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Artificial intelligence in education: A systematic literature review

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ABSTRACT

Artificial intelligence (AI) in education (AIED) has evolved into a substantial body of literature with diverse perspectives. In this review paper, we seek insights into three critical questions: (1) What are the primary categories of AI applications explored in the education field? (2) What are the predominant research topics and their key findings? (3) What is the status of major research design elements, including guiding theories, methodologies, and research contexts? A bibliometric analysis of 2,223 research articles followed by a content analysis of selected 125 papers reveals a comprehensive conceptual structure of the existing literature. The extant AIED research spans a wide spectrum of applications, encompassing those for adaptive learning and personalized tutoring, intelligent assessment and management, profiling and prediction, and emerging products. Research topics delve into both the technical design of education systems and the examination of the adoption, impacts, and challenges associated with AIED. Furthermore, this review highlights the diverse range of theories applied in the AIED literature, the multidisciplinary nature of publication venues, and underexplored research areas. In sum, this research offers valuable insights for interested scholars to comprehend the current state of AIED research and identify future research opportunities in this dynamic field.

1. Introduction

Information technologies, particularly artificial intelligence (AI), are revolutionizing modern education. AI algorithms and educational robots are now integral to learning management and training systems, providing support for a wide array of teaching and learning activities (Costa et al., 2017; García et al., 2007). Numerous applications of AI in education (AIED) have emerged. For example, Khan Academy offers Khanmigo, an AI tutor harnessing GPT-4 capabilities, delivering personalized learning support and intelligent feedback across various subjects, including mathematics, programming, and language learning. Similarly, Duolingo, a language learning platform, uses sophisticated AI systems to improve learner experiences (Bicknell et al., 2023). iFlyTek offers intelligent assessment systems tailored for various grading scenarios, including the national college entrance examination in China (iFlyTek, 2024). AI-powered learning management systems (LMS), such as Absorb LMS and Docebo, deliver multiple AI capabilities to support teaching and learning activities, such as intelligent content creation, administrative task automation, and personalized learning (Leh, 2022). In the realm of educational robots, SoftBank Robotics Nao and Pepper robots are developed to serve as language-teaching social robots (Belpaeme & Tanaka, 2022).

The applications of AIED are rapidly evolving, reshaping the overall teaching and learning landscape (Popenici & Kerr, 2017). The advent of generative AI technologies has introduced further opportunities, attracting investment into and development of the AIED industry. The global AIED market, valued at USD 1.82 billion in 2021, is projected to grow at a compound annual rate of 36 % from 2022 to 2030 (GrandViewResearch, 2021). Learners, teachers, and educational institutions are quickly embracing AIED. Recent statistics indicate that 43 % of college students in the US use AI tools like ChatGPT and half of instructors employ AI to develop their lessons (Businessolution.org, 2023).

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Moreover, AIED demonstrates its efficacy and effectiveness. Adaptive learning enabled by AIED has been shown to improve student test results by 62 %, while AI usage, in general, enhances student performance by 30 % and reduces anxiety by 20 % (Businessolution.org, 2023).

Concurrently, research on AIED has surged in recent years, yielding a substantial body of work exploring various aspects of these applications, including design, effectiveness, and outcomes (Chiu et al., 2023). This burgeoning research landscape has attracted review studies, which offer insights into the general AIED research field (Chassignol et al., 2018; Goksel & Bozkurt, 2019; Guan et al., 2020; Hwang et al., 2020; Srinivasan, 2022) as well as specific topics such as learning analytics (Charitopoulos et al., 2020), machine learning and precision education (Luan & Chin-Chung, 2021), or educational AI within particular subject areas such as mathematics (Hwang & Tu, 2021) or STEM (Xu & Ouyang, 2022). Nonetheless, few studies have systematically delineated the conceptual structure of the AIED research field and its theoretical underpinnings, which are pivotal for understanding its current state and evolving prospects.

This review aims to provide an in-depth understanding of the conceptual structure of existing AIED research. Specifically, it addresses the following research questions:

(1) What are the primary categories of AI applications explored in the education field?
(2) What are the predominant research topics and their key findings?
(3) What is the status of major research design elements in the AIED field, including research methods, guiding theories, and research contexts?

For these questions, this research employs a mixed research methodology, combining a bibliometric analysis (Donthu et al., 2021) with a systematic literature review (Snyder, 2019). Bibliometric analysis involves the quantitative summarization of metadata of extensive research articles, including publication year, title, abstract, citations, authors, and institutions. It serves as an efficient method for grasping the state of a research field, particularly when the review scope is broad and the dataset is too extensive for manual examination (Donthu et al., 2021). In contrast, a systematic literature review, through content analysis of research articles, can delve into research nuances that are of interest to researchers (Snyder, 2019). Together, these two complementary approaches can provide a comprehensive view of the conceptual structure and emerging trends in the research field (Donthu et al., 2021).

This research starts with a bibliometric analysis of 2,223 papers within the general topic of AIED. The descriptive analysis of the bibliometric metadata offers insights into publication trends, influential journal sources, and key articles. To gain a comprehensive understanding of emerging research concepts, we provide the co-occurrence networks of two types of keywords that are associated with articles: keywords plus and author keywords. Next, we selected and coded 125 empirical research articles for a systematic literature review, including AIED applications, research topics, and other research design details, such as research methodologies, background theories, and research contexts.

The coding results show four primary categories of AI applications within the AIED literature, including adaptive learning and personalized tutoring, intelligent assessment and management, profiling and prediction, and emerging products, with adaptive learning and personalized tutoring being the most studied. The research topics range from system design and implementation, adoption and use, AIED impacts, and its challenges, with system design and implementation being the most popular topic. The coding also reveals that experiments are the most frequently used research methodology, and several learning theories, including constructivist learning theory, learning style theory, cognitive theories of learning, and item response theory, are among the most employed theories that guide the research design. Higher education is the most frequent research context.

This research contributes to the literature of AIED in multiple ways. First, it offers a comprehensive understanding of the conceptual structure of the AIED research, filling a gap in existing work. Moreover, in light of the recent trend of a substantial surge in AIED research articles and the review works on specific AIED domains, this study provides a critical, up-to-date overview of the evolving research landscape, incorporating the latest articles. Additionally, the examination of the current status of AIED research has unveiled underexplored research areas and highlighted essential future research directions. These include the integration of new AI technologies, the elevation of theoretical contributions in research, and the enhancement of scientific rigor through theory-guided research design. These valuable insights may lend useful assistance in shaping the development of the AIED research field.

This research is structured as follows. First, we provide a literature review of existing review studies in the AIED research field. Second, we detail the process and results of the bibliometric analysis. We then present a systematic literature review of a selected set of empirical research on AIED, offering insights into categories of AIED applications, primary research topics, and common research design elements. We conclude with a discussion of the major outcomes and the contributions of this study.

2. Literature review

AI is a subfield of computer science dedicated to understanding human thought processes and recreating their effects through information systems. The primary goal of AI is to create intelligent systems (i.e., computer programs or machines) that are capable of intelligent behaviors (Rainer et al., 2016), including learning, reasoning, problem-solving, perception, and creating. Typical examples of AI technologies include expert systems, neural networks (including machine learning and deep learning techniques), fuzzy logic, genetic algorithms, and intelligent agents (Rainer et al., 2016). Scholars often distinguish between strong and weak AI (Wells, 2023). Strong AI, also known as artificial general intelligence, possesses a broad spectrum of human capabilities, including communication, reasoning, and emotional responses, and is capable of multiple tasks. In contrast, weak AI, also known as narrow AI, does not possess a full array of human capabilities but can use algorithms to solve problems or reason for specific tasks, such as fraud detection and chess playing. AI applications that have been currently developed and brought into commercial use are categorized as weak AI.

The field of education especially lends itself to AI technologies since educational activities, including learning and teaching, are knowledge-intensive cognitive activities, and AI applications, which are created for cognition and problem-solving based on algorithms and knowledge base, can effectively support and augment educators' and learners' abilities in teaching and learning. Since the advent of AI in the mid-1950 s, AI technologies have been increasingly applied to facilitate education and training in various subjects, including language, STEM, and medicine (Perrotta & Selwyn, 2020). To date, AIED applications are developed to support teaching and learning activities such as content preparation and dissemination, interactions and collaboration, and performance assessment (Chassignol et al., 2018; Perrotta & Selwyn, 2020).

A substantial body of studies has examined AIED applications, leading to review studies in the field. Table 1 provides a list of recent review articles. Several reviews pertain to the general field of AIED (Chassignol et al., 2018; Chen, Xie, & Hwang, 2020; Chen, Xie, Zou, et al., 2020; Chiu et al., 2023; Goksel & Bozkurt, 2019; Guan et al., 2020), while most focus on a specific application area such as chatbot (Okonkwo & Ade-Ibijola, 2021), precision education (Luan & Chin-Chung, 2021), mathematics education (Hwang & Tu, 2021), STEM (Xu & Ouyang, 2022), or student assessment (González-Calatayud et al., 2021). Scholars have used bibliometric, systematic or simply narrative reviews in their investigation of the field. For example, through a

Table 1
Literature Review: Major Review Studies in Recent Years.

Article	Type	Review content	Time of articles reviewed	Research domain
Kulik & Fletcher, 2016	Systematic review of 50 papers	Synthesized and analyzed the effect sizes of the effectiveness of intelligent tutoring systems	Not specified	Intelligent tutoring systems
Chassignol et al., 2018	Narrative review	Developed a framework that classifies AIED applications by different components of education process: content, teaching methods, assessment and communication	Not specified	General
Zhang et al., 2018	Bibliometric study of 1,579 papers	Conducted descriptive analyses of bibliometric data, including top authors and journals; Summarized four methods in learning analytics and their evolution patterns.	1995–2008	Learning analytics
Hinojo-Lucena et al., 2019	Bibliometric study of 132 papers	Conducted a descriptive study of bibliometric data, including publication trend, sources, authors, organizations, and countries	2007–2017	Higher education
Zawacki-Richter et al., 2019	Systematic review of 146 papers	Conducted descriptive analyses of bibliometric data, including publication trends, journals, countries, author affiliation and methods; Summarized AIED applications.	2007–2018	Higher education
Charitopoulos et al., 2020	Systematic review of 316 papers	Coded education problems addressed, learning contexts, soft computing methods employed and major journal outlets for each area of educational data mining and learning analytics	2010–2018	Educational data mining and learning analytics research
Chen, Xie, & Hwang, 2020	Bibliometrics of 9,560 papers	Conducted a descriptive study of bibliometric data, including grants, conferences, journals, software tools, institutions, and researchers	1999–2019	General
Chen, Xie, Zou, et al., 2020	Systematic analysis of 45 papers	Reviewed publication journals, citation counts, regions and institutions of authors, application scenario types, research issues, adopted AI technologies, and definitions concerned	1990–2016	General
Guan et al., 2020	Computer-assisted text analysis and manual content analysis of 425 papers	Reviewed research themes over two stages (i.e., 2000–2009 and 2010–2018).	2000–2019	General
González-Calatayud et al., 2021	Systematic review of 22 papers	Reviewed AI definition, pedagogical models used, reasons for using AI, the use of automated scoring, and comparison of assessment evaluation accuracy between AI use and non-use	2010–2020	AI for student assessment
Hwang & Tu, 2021	Bibliometric mapping analysis and systematic review of 43 papers	Reviewed publication journal, paper citations, cited authors, keywords, application domains, sample groups, research methods, roles of AI, adopted AI algorithms and research issues	1996–2020	AI in mathematics education
Luan & Chin-Chung, 2021	Systematic review of 40 empirical papers	Reviewed multiple elements of research papers, including research purpose, education context, data sources, learners' individual differences, learning outcomes, learning algorithms, evaluation of algorithms, and major research findings	2016–2020	Machine-learning-based precision education
Okonkwo & Ade-Ibijola, 2021	Systematic review of 53 papers	Summarized types of chatbot applications, their benefits, implementation challenges, and potential future areas	2015–2021	Chatbots in education
Celik et al., 2022	Systematic review of 44 papers	Reviewed the role of teachers in AIED, the advantages that AI offers teachers, the challenges teachers face when using AI, and AI methods in AI-based research with teachers	2004–2020	Teachers' perspective
Xu & Ouyang, 2022	Systematic review of 63 empirical AI-STEM studies	Summarized AI applications in STEM education and their associated elements such as educational information (content), subjects (leaners and instructors), medium, and environment	2011–2021	AI in STEM education
Chiu et al., 2023	Systematic review of 92 papers	Summarized AIED applications and outcomes, including applications in the domains of learning, teaching, assessment and admin, and outcomes related to teachers and learners	2012–2021	General

narrative review, Chassignol et al. (2018) summarized and presented their major literature findings in a framework with four components of the educational process: content, teaching method, assessment, and communication. Goksel and Bozkurt (2019) conducted a co-word analysis of the keywords in 393 papers between 1970 and 2018, summarizing three key concepts in the AIED literature, including adaptive learning, personalization and learning styles, and expert systems and intelligent tutoring systems. Xu and Ouyang (2022) conducted a systematic review of 63 empirical AI-STEM research from 2011 to 2021, summarizing AI applications in STEM education, their characteristics and effects.

Despite existing review studies on AIED research, there is a need for a comprehensive review of the up-to-date literature to gain insights into the conceptual structure of the field. First, the majority of the existing review focuses on AIED applications and their characteristics (Chassignol et al., 2018; Chiu et al., 2023; Xu & Ouyang, 2022), missing a higher-level comprehensive overview of research topics and methodologies, which is key to scholarly interest. Second, existing review studies on the general AIED field are mainly based on the sample of articles before 2019. However, the COVID-19 pandemic spurs the adoption of AI and the research of AIED. This up-to-date sample needs to be reviewed and their insights aggregated. Finally, there is a lack of examination of the foundational theories that are commonly employed in and steering the AIED research, which are critical in comprehending the current body of studies and charting future research development.

3. Bibliometric analysis of AI in education research

3.1. Data collection

This research uses the Web of Science (WoS) database to compile an initial set of papers. The WoS database is a commonly employed resource for conducting systematic literature reviews. Following the methodology outlined by Goksel and Bozkurt (2019), we conducted a search in WoS in June 2022 to retrieve English publications that contain the terms "artificial intelligence" and "education" in their title, abstract, or keywords. This initial search yielded a total of 3,690 articles. We then performed a manual screening to assess the relevance of these articles to our focus on AIED. Any publications deemed irrelevant or lacking substantial content on AIED were removed from our dataset. Additionally, we retained only scholarly works with full-text access, encompassing journal articles and conference papers. The final dataset comprised 2,223 articles published between 1984 and June 2022. Subsequently, we performed a bibliometric analysis of these 2,223 articles utilizing the R package "bibliometrix" and its interactive web version "biblioshiny", as developed by Aria and Cuccurullo (2017).

3.2. Descriptive analysis of bibliometric data

Table 2 summarizes the basic information of the articles in our dataset. The publication dates of the 2,223 articles span from 1984 to June 2022. These articles were published across 1,247 journals and collectively cite 60,764 references. In June 2022, the average age of these articles was 5.62 years, indicating that over half of the AIED research papers were published after 2016. To further investigate the publication trends in AIED, Fig. 1 illustrates the growth of this field. Notably, AIED did not emerge as a prominent research area until 2017. The annual publication counts never exceeded 50 articles from 1984 to 2016. However, since 2017, this field has garnered considerable research attention, experiencing a significant surge between 2019 and 2021. This growth can be attributed to the rapid advancement of AI capabilities in recent years (Roser, 2022) and the transformation to online teaching during the COVID-19 pandemic (Du et al., 2022).

An examination of the top-cited journals and articles reveals further insights. Fig. 2a lists the top 10 journals that publish the most numbers of articles in our sample, and Fig. 2b shows the top 10 locally cited sources (i.e., journals cited by the articles in our sample). The two journal lists demonstrate that AIED is a cross-disciplinary field. Research is published in Computer Science journals (such as *Journal of Intelligent and Fuzzy Systems*, *Wireless Communications and Mobile Computing*, *IEEE Access*), Education journals (such as *International Journal of Emerging Technologies in Learning*, and *Computer and Education*), and Management Information Systems (MIS) journals (such as *Computer in Human Behavior*). Comparing Fig. 2a and 2b shows that open-access journals have served as a major outlet for AIED research in terms of the number of papers published—9 out of the 10 journals shown in Fig. 2a are open-access journals (except for *Journal of Intelligent and Fuzzy Systems*), whereas traditional, established journals such as *Computer and Education* and *Computers in Human Behavior* are more impactful in terms of citations they attract. Both open-access journals and traditional journals contribute to the dissemination of knowledge on AIED.

To gain further insights into the impactful work in AIED, we summarize the top 15 globally cited papers, the top 15 locally cited papers, and the top 15 cited references in our sample in Fig. 3a, 3b, and 3c, respectively. The full information of these papers is provided in the Appendix. The top globally and locally cited papers cover a range of themes in AIED, which can be roughly classified into three categories, including (1) general opinion papers (Dwivedi et al., 2020; Gadanidis, 2017) and literature reviews (Chen et al., 2020; Hinojo-Lucena et al., 2019; Zawacki-Richter et al., 2019); (2) research on popular AIED applications, including machine learning and precision education (Costa et al., 2017; Duong et al., 2019), intelligent tutoring (Nwana, 1990), learning companion agents (Chou et al., 2003), chatbots (Fryer et al., 2017), and educational robotics (Murphy, 2001); (3) research on perception and attitude towards AI systems (Sit et al., 2020).

An examination of the top 15 cited references by the papers in our sample (see Appendix 1c) reveals the disciplinary foundations of AIED research. Except for the above-mentioned AIED topics, classic work in fields of computer science and AI, MIS, and education are cited, including Turing's (1950) impactful work on machine intelligence, Russell and Norvig's (2002) popular textbook on AI, David's (1989) classic paper on user adoption and behavior towards information systems, and Felder's (1988) widely cited paper on teaching and learning styles. These cited references suggest three disciplines foundational to AIED research: Computer Science and AI, MIS, and Education.

Table 2
Article Information in the Sample.

Description	Results
Timespan	1984:2022(June)
Journals included	1,247
Articles included	2,223
Average years from publication	5.62
Average citations per documents	4.09
Cited references	60,764
Keywords plus (ID)	1,336
Author keywords (DE)	5,076

To further identify the impacts of the papers in our sample, Fig. 4 illustrates the average article citation per year (AACPR). AACPR represents the total number of citations received by papers published in a specific year, normalized by citable years (i.e., the number of years since publication). This normalization accounts for the fact that older publications tend to accumulate more citations over time. Normalizing citations in this way can mitigate the age effect when assessing paper quality based on citations. As shown in Fig. 4, AACPR demonstrates an upward trend for papers published since 2014. This indicates that recent publications tend to attract more citations than their older publications, suggesting a growing impact of recent research in the field.

In addition, Fig. 4 marks specific papers that contribute to notable spikes in the AACPR trend line. The highest spike occurs in 1990. In our sample, only one paper, namely, Nwana (1990) review article on intelligent tutoring systems is from that year. This paper has garnered a substantial number of citations, underscoring both its quality and the enduring interest in the topic of intelligent tutoring systems over the past 28 years. Other heavily cited papers include Chou et al.'s (2003) research on learning companions and educational agents, García et al.'s (2007) study on students' learning styles detection, and Dwivedi et al.'s (2020) commentary on the impact of COVID-19 on education. These papers have significantly contributed to the scholarly discourse in AIED.

3.3. Keyword co-occurrence analysis

To understand the conceptual structure of the literature, we conduct keyword co-occurrence analysis, also known as co-word analysis. In this analysis, a co-word network is constructed, where nodes represent keywords, edges signify co-occurrence relationships, and edge weights indicate the frequency of co-occurrences within the literature body. Keywords provide concise summaries of research works and are well-suited for co-occurrence analyses, allowing us to discover structural patterns among core concepts in the literature. Our analysis utilizes both keywords plus and author keywords available in WoS: keywords plus are standardized keywords provided by WoS, and author keywords are provided by authors in their articles. Prior to the analysis, we preprocess and clean the keywords, making necessary adjustments such as replacing "AI" with "artificial intelligence" and standardizing both "student" and "students" to "students".

Fig. 5 illustrates the distributions of the top 50 keywords plus and author keywords in panels a and b, respectively. Notably, "artificial intelligence" and "education" occupy the top two positions in both panels, as these were the primary search terms used to identify the literature body. Beyond these two keywords, the lists of keywords plus and author keywords exhibit significant differences, with author keywords being more diverse and closely tied to the content of the articles. First, keywords plus are more broadly descriptive, while author keywords are more specific to article content. For instance, the top keywords in keywords plus, excluding the top 2, consist of general terms such as "system", "students", "performance", "design", "technology", "models", and "sciences". In contrast, author keywords delve into specialized niche areas within AIED, including terms like "machine learning", "higher education", "e-learning", "intelligent tutoring system", and "robotics". Second, the distribution of author keywords is more skewed than that of keywords plus. The distribution of author keywords is heavily biased towards the two search keywords, "artificial intelligence" and "education". This skewness is probably due to the greater diversity and less standardized nature of author keywords compared to keywords plus.

3.3.1. Co-occurrence network of keywords plus

To further discover the conceptual patterns of the literature, we

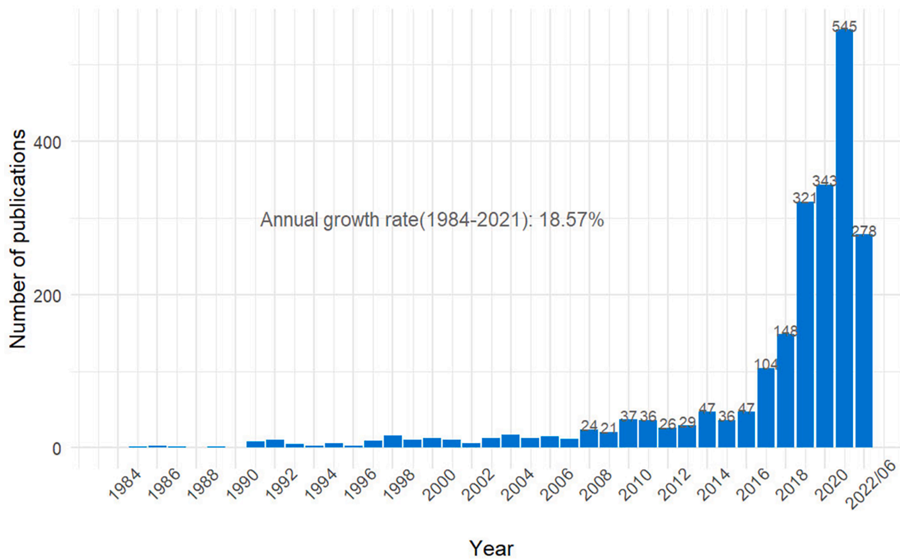
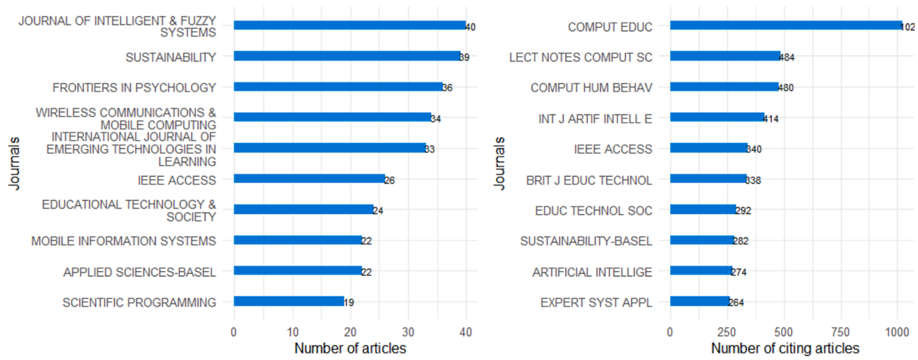


Fig. 1. Annual Scientific Production (Note: bars with number of publications less than 20 are not labelled).



(a) Top Journals Publishing AIED Research **(b) Top Local Cited Journals**

Fig. 2. Important Journal .
Sources

provide the co-occurrence network of the two types of keywords in Fig. 6. The network analysis was carried out using the biblioNetwork() function within the R bibliometrix package. The network includes the top 50 nodes, and clusters were identified using the Louvain clustering algorithm. Fig. 6a displays the results for the keywords plus co-occurrence network analysis, revealing four distinct concept clusters: user behaviors, design science, big data analytics, and AIED impacts.

The user behaviors cluster primarily revolves around user intentions and behaviors towards AIED systems, such as system adoption and use behaviors. Typical keywords within this cluster include "behavior", "perceptions", "user acceptance", "intention", and "engagement". Some keywords, such as "health", "language", "children", and "higher education", point to the contexts of studies. That is, health(care)-related education, language education, children's education, and higher education are focal research contexts of AIED behavior research.

The design science cluster predominantly concerns the design and implementation of AIED systems and tools. Key terms associated with this cluster encompass "design", "science", "implementation", "feedback", and "tools". Some keywords indicate the current technological trends upon which these systems are constructed, including "augmented reality", "virtual reality", and "tutoring systems". The term "knowledge" frequently co-occurs, possibly signifying the importance of establishing knowledge bases and knowledge mapping within AIED systems.

The big data analytics cluster mainly focuses on constructing systems, models, frameworks, and environments that utilize big data and algorithms to make predictions within the educational context. Keywords associated with this cluster consist of "model", "framework", "system", "environment", "algorithms", "big data", and "analytics". Additionally, the term "classification" is frequently co-occurring, suggesting that classification algorithms are commonly used within this research domain.

The AIED impacts cluster pertains to the influence of AI, particularly its impact on learner skills, learning quality, and experiences resulting from the use of new technologies or technology-supported simulated learning environments. Relevant keywords encompass "experience", "skills", "impact", "quality", "simulation", and "challenges". The term "perspectives" emerges within this cluster, indicating that the impact is viewed from multiple angles. This cluster aligns with the concept of "21st-century skills", as identified by (Chiu et al., 2023) in their systematic review of the impacts of AIED. Their research suggests that AIED can help students acquire problem-solving and online collaboration skills, enhancing learning quality.

3.3.2. Co-occurrence network of author keywords

The results of the author keyword co-occurrence network analysis are more varied and less coherent than those from the keywords plus co-

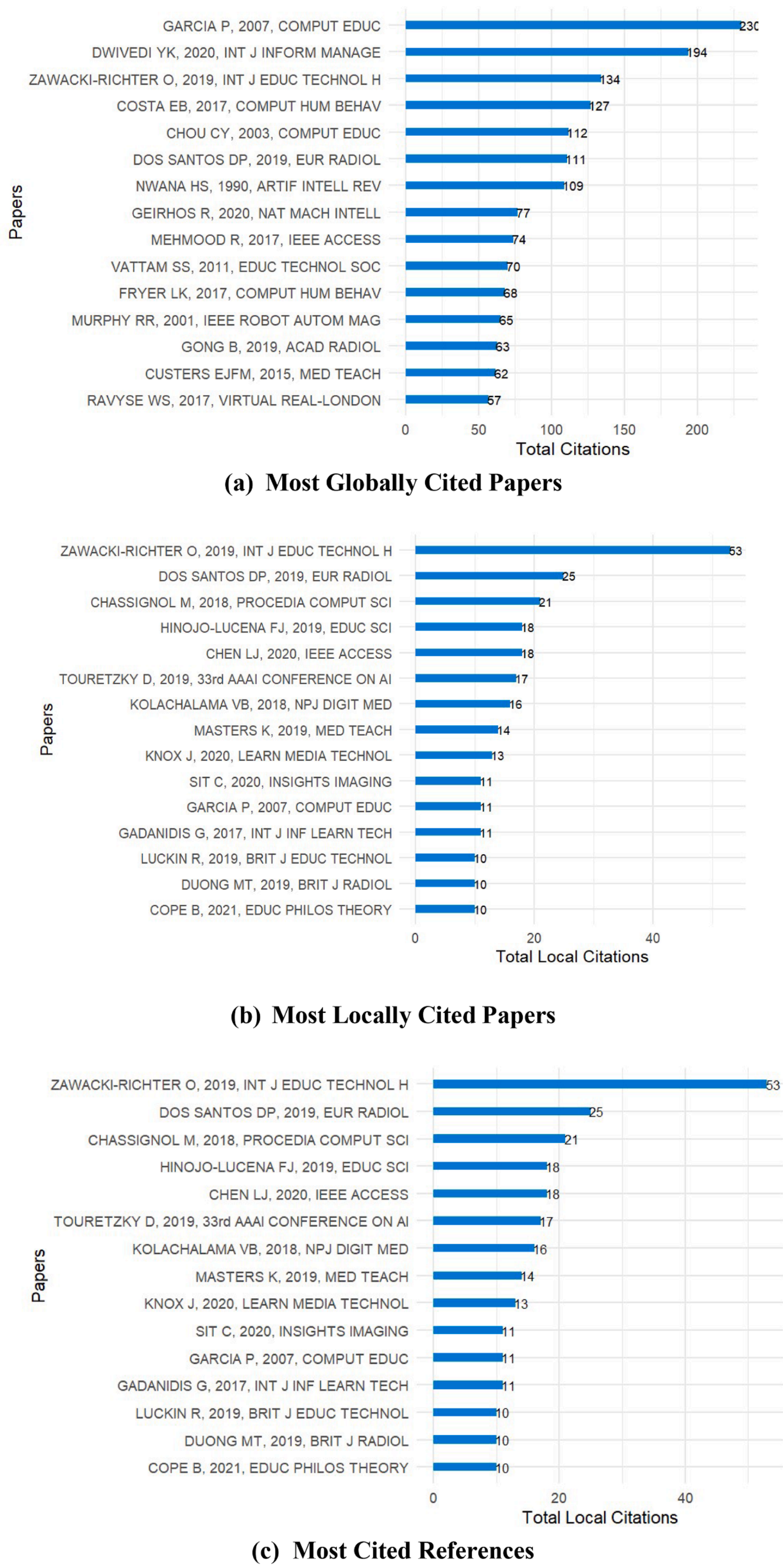
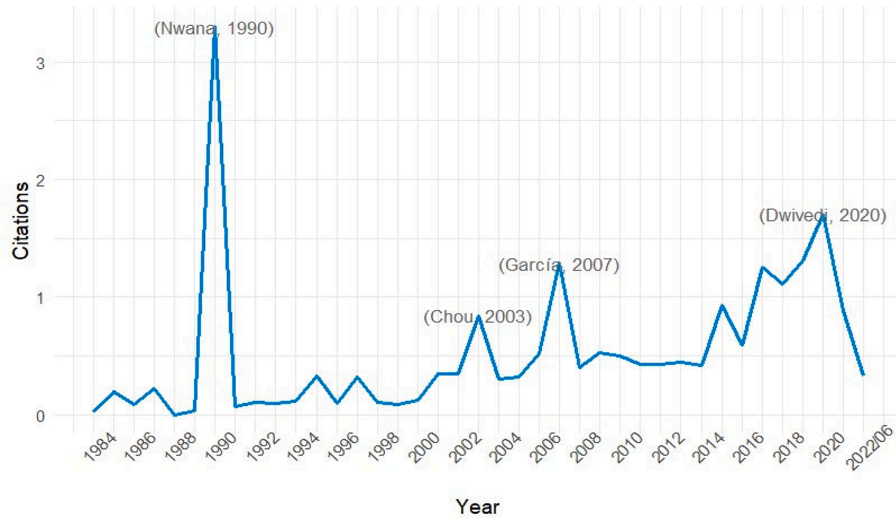


Fig. 3. Most Cited Papers and References.

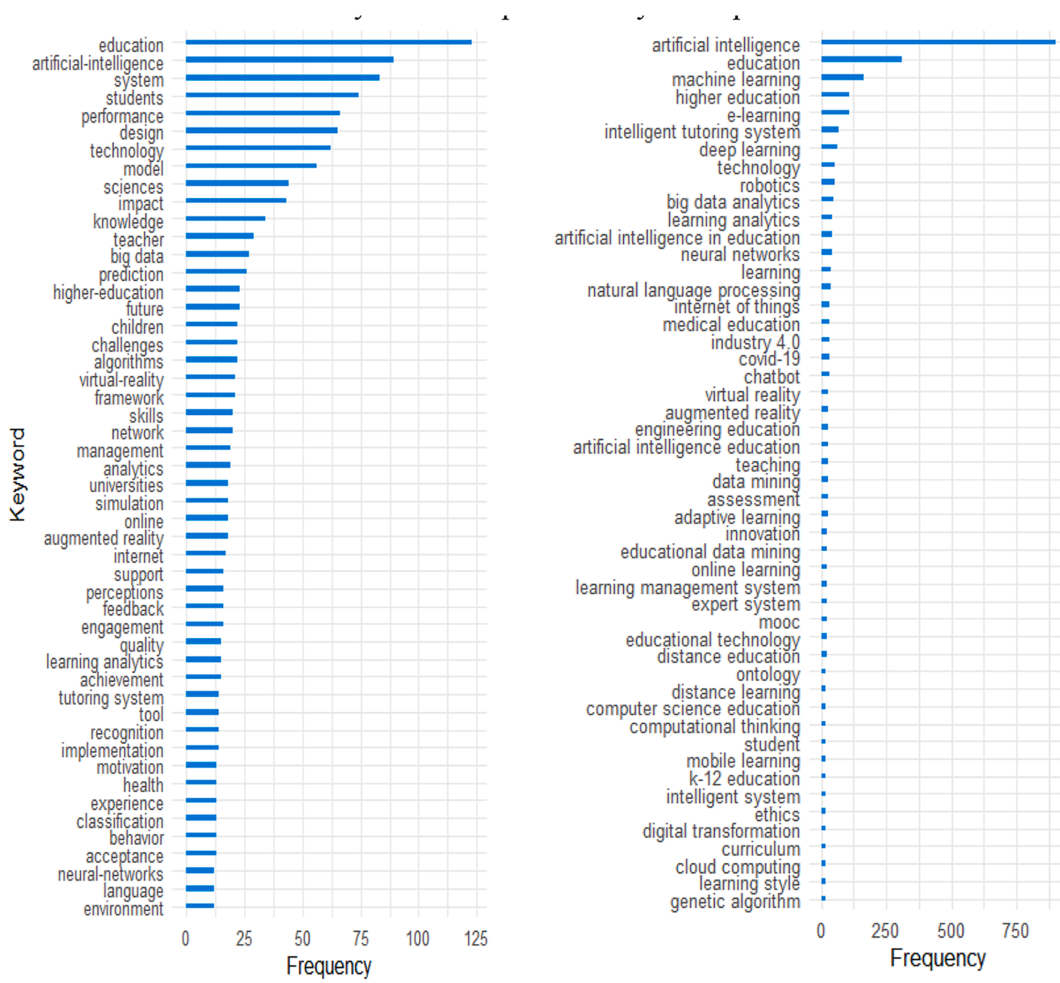
occurrence analysis, primarily because author keywords are diverse in nature. To avoid potential bias from the dominance and significant skewness of the top two search terms, "artificial intelligence" and "education," as shown in the above keyword distribution analysis, we excluded these terms from the network analysis. Fig. 6b presents the co-occurrence network analysis result, revealing five distinct concept clusters: machine learning, educational technology, learning systems, emerging technologies, and AI education.

The machine learning cluster primarily focuses on the application of data science and AI technologies for educational data mining and learning analytics. This cluster includes terms related to AI techniques such as "machine learning", "deep learning", "neural networks",



Note: Papers noted at the peaks are the most significant contributors to the AACPY of that particular year.

Fig. 4. Average Article Citation Per Year (AACPY).

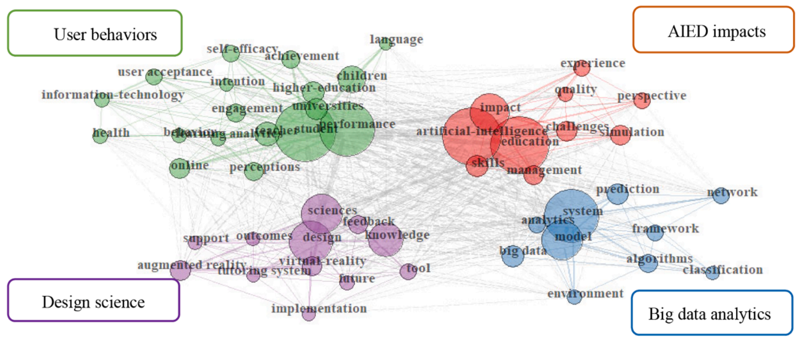


(a) Keyword Plus **(b) Author Keywords**

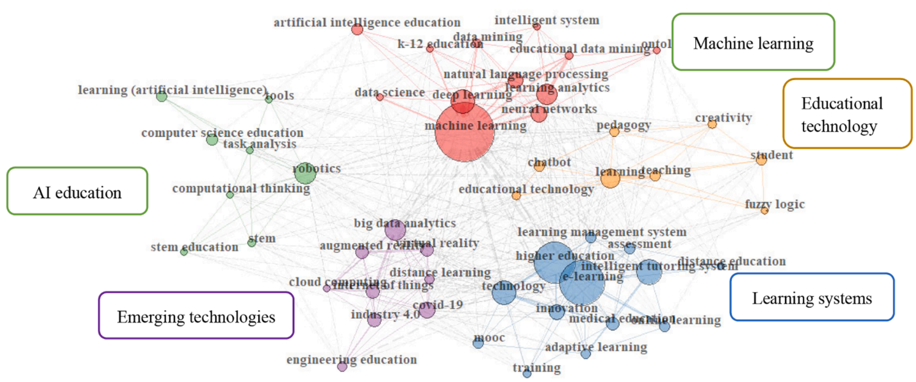
Fig. 5. Most Frequent Keywords.

"natural language processing", and "intelligent systems". It also incorporates the term "K-12 education", indicating a main context of study in the machine learning cluster.

The educational technology cluster centers on the use of AI technology to enhance teaching and learning, with a particular emphasis on implementing AI such as pedagogical agents and intelligent pedagogical



(a) Keyword Plus



(b) Author Keywords

Fig. 6. Keyword Co-occurrence Networks.

assistance system to support creative and innovative pedagogical practices. Two AI techniques, "chatbot" and "fuzzy logic", are frequently associated with research in this cluster.

The learning systems cluster is primarily concerned with the development of innovative learning support systems, including intelligent tutoring systems and learning management systems. Adaptive learning is a prominent direction of innovation within this cluster. Additionally, terms such as "MOOC", "distance education", "online learning", and "higher education" are frequently used as the contexts of studying learning systems.

The emerging technologies cluster contains a list of emerging technologies relevant to AIED, including "big data analytics", "augmented reality", "virtual reality", "cloud computing", "internet of things", and "industry 4.0″. Contextual terms like "COVID-19″, "distance learning", and "engineering education" are associated with this cluster, indicating that the COVID-19 pandemic and the resulting shift to distance learning have accelerated the applications and research related to emerging technologies.

The AI education cluster primarily focuses on the education and learning of AI-related knowledge and skills. These include STEM and computer science-related knowledge and skills, such as "learning artificial intelligence", "tools", "computer science education", "task analysis", "robotics", and "computational thinking".

The keyword co-occurrence analysis serves as a foundational tool for comprehending the central concepts within the literature. Both analyses have identified common concept clusters, which are summarized on the left side of Fig. 7. Notably:

The big data analytics cluster in the keywords plus co-occurrence network relates to the machine learning cluster in the author keyword network. However, the machine learning cluster delves deeper into machine learning concepts compared to the more general terms like "models" and "frameworks" in the big data analytics cluster.

The educational technology, learning systems, and emerging technologies clusters in the author keyword network collectively correspond to the broader design science cluster in the keywords plus network, yet reflect different focuses in research. The educational technology, learning systems, and emerging technologies clusters in the author keyword network are concepts associated with AIED applications, while the design science cluster in the keywords plus network seems to suggest the potential research topic on designing these applications.

The AIED impacts cluster in the keywords plus network is associated with the AI education cluster in the author keyword network, as both focus on studying the knowledge and skills associated with AIED. However, the AI education cluster delves into more detailed skills and disciplinary knowledge for students to learn about AI, while the AIED impacts cluster focuses on skills learned as a result of using AIED applications.

Interestingly, the user behaviors cluster does not prominently emerge in the author keyword network. This may be attributed to the less standardized nature of author keywords and the inclusion of only the top 50 nodes in the network for clarity. Behavior keywords may be wide-ranged in the author keywords, and thus do not prominently appear in the top 50 nodes.

These findings provide valuable insights into the distribution of research topics and concepts within the AIED literature, highlighting the prevalence and distinctiveness of several important research areas.

4. Content analysis

Bibliometric analysis is inherently data-driven and does not probe

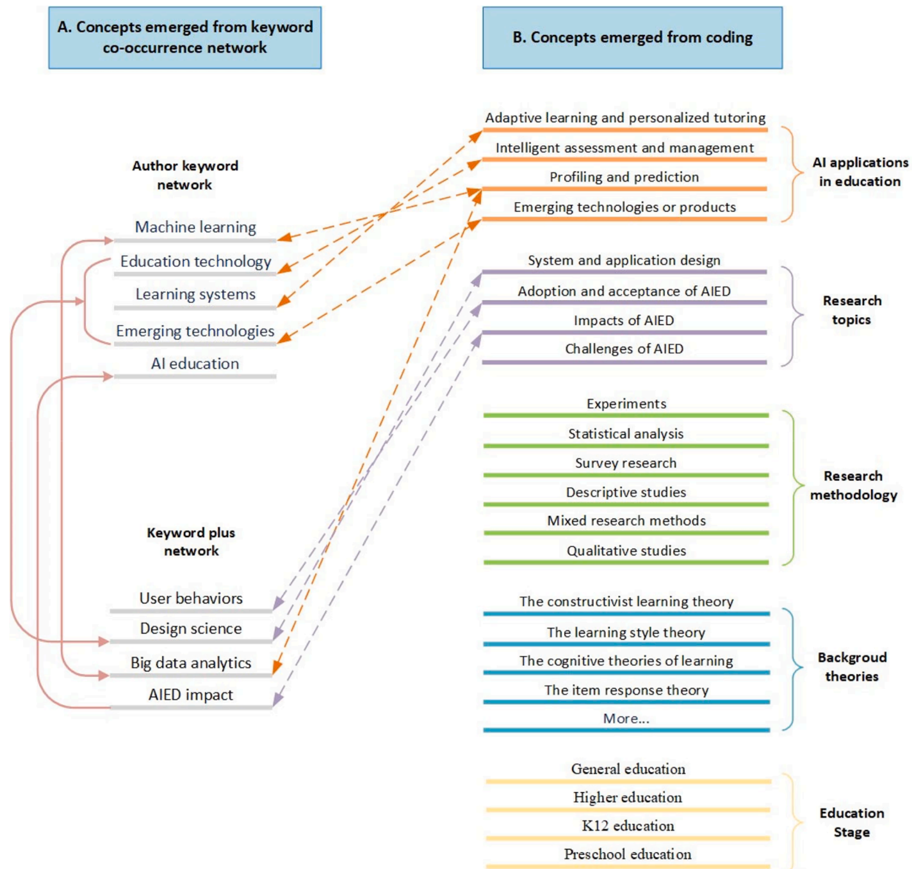


Fig. 7. Conceptual Mapping between Co-occurrence Networks and Systematic Review.

into the content details of research articles. Consequently, we complement the bibliometric analysis with a systematic literature review that involves manual content analysis of a smaller sample of articles. The results obtained from the co-occurrence network analysis serve as a foundation for coding the selected papers in the systematic review. The results pertaining to research designs from the content analysis are summarized on the right side of Fig. 7. Fig. 7 also illustrates a mapping between concepts derived from the co-occurrence network analysis and those derived from the systematic analysis of the selected papers.

4.1. Paper selection and analysis

To select a subset of papers for content analysis from the initial pool of 2,223 papers used in the bibliometric analysis, we applied the following criteria: (1) Papers that are published in journals of the category quartile Q1 in the Journal Citation Reports; (2) Papers that clearly describe the AI applications under study and report their impact on teaching and learning; and (3) Papers that contain an empirical study. We focus on empirical studies because they go beyond conceptual understanding and provide empirical evidence in addressing specific research questions. Understanding their content and research methods

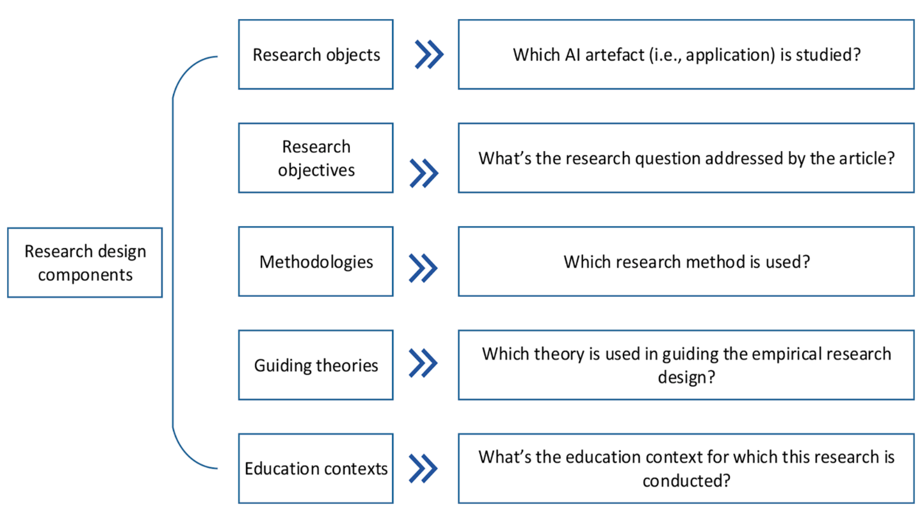


Fig. 8. Coding Schema.

can provide valuable insights into the development of the AIED research field and guide future research. A total of 125 papers were identified for content analysis.

As illustrated in Fig. 8, we coded common components of research design in each article. These components included research objects, objectives, methodologies, guiding theories, and educational contexts.

4.2. Results of content analysis

Fig. 9 illustrates the distributions of various types of AIED applications, research topics, research methods, guiding theories, and education contexts coded in the subset of papers in content analysis.

4.2.1. Research objects: AI applications in education

As depicted in Fig. 9a and Fig. 10, we have identified four primary categories of AIED applications, each with its corresponding sub-categories: (1) Adaptive learning and personalized tutoring, (2) Intelligent assessment and management, (3) Profiling and prediction, and (4) Emerging technologies or products. Among all applications (shown in Fig. 9a), the most studied are adaptive learning and personalized tutoring applications (40 % of papers in our sample), followed by intelligent assessment and management applications (24.8 %), profiling and prediction applications (20 %), and emergent products in education (15.2 %).

4.2.1.1. Adaptive learning and personalized tutoring applications. This category of AIED applications aims to customize the learning process and create an adaptive learning environment for learners based on their knowledge level, learning style, emotional state, and interest preferences. These applications have evolved significantly in recent years, transitioning from rule-based expert systems to more complex AI techniques and algorithms like neural networks and decision trees. The design of these applications has become increasingly interactive and learner-centered. Two sub-categories of adaptive learning and personalized tutoring applications include intelligent tutoring systems and adaptive hypermedia learning systems.

Intelligent tutoring systems (ITS) are computer-assisted instructional systems that harness the power of AI technologies to emulate the role of a human tutor. These systems are designed to offer immediate and personalized instruction or feedback to students under specific educational strategies (Hooshyar et al., 2015). ITS research frequently mentions about "intelligent tutor", "intelligent tutoring system" (Aleven et al., 2009), and "intelligent agent" (Xu & Wang, 2006). The functions of ITS applications, as studied in the 34 articles within our sample, can be categorized into three primary types: learner status diagnosis and adaptive feedback provision (n = 24), adaptive test and exercise provision (n = 5), and adaptive learning content recommendation (n = 5).

Like a human tutor, ITS can monitor and diagnose learners' learning progress and provide targeted feedback and guidance. For instance, Gülcü (2009) proposed and tested "ZOSMAT", a mathematical tutoring system that tracks a student's learning journey and offers personalized guidance based on their performance. Leveraging AI technology, educators can provide specialized support to learners experiencing difficulties, ultimately achieving precision education (Lin & Lai, 2021). In

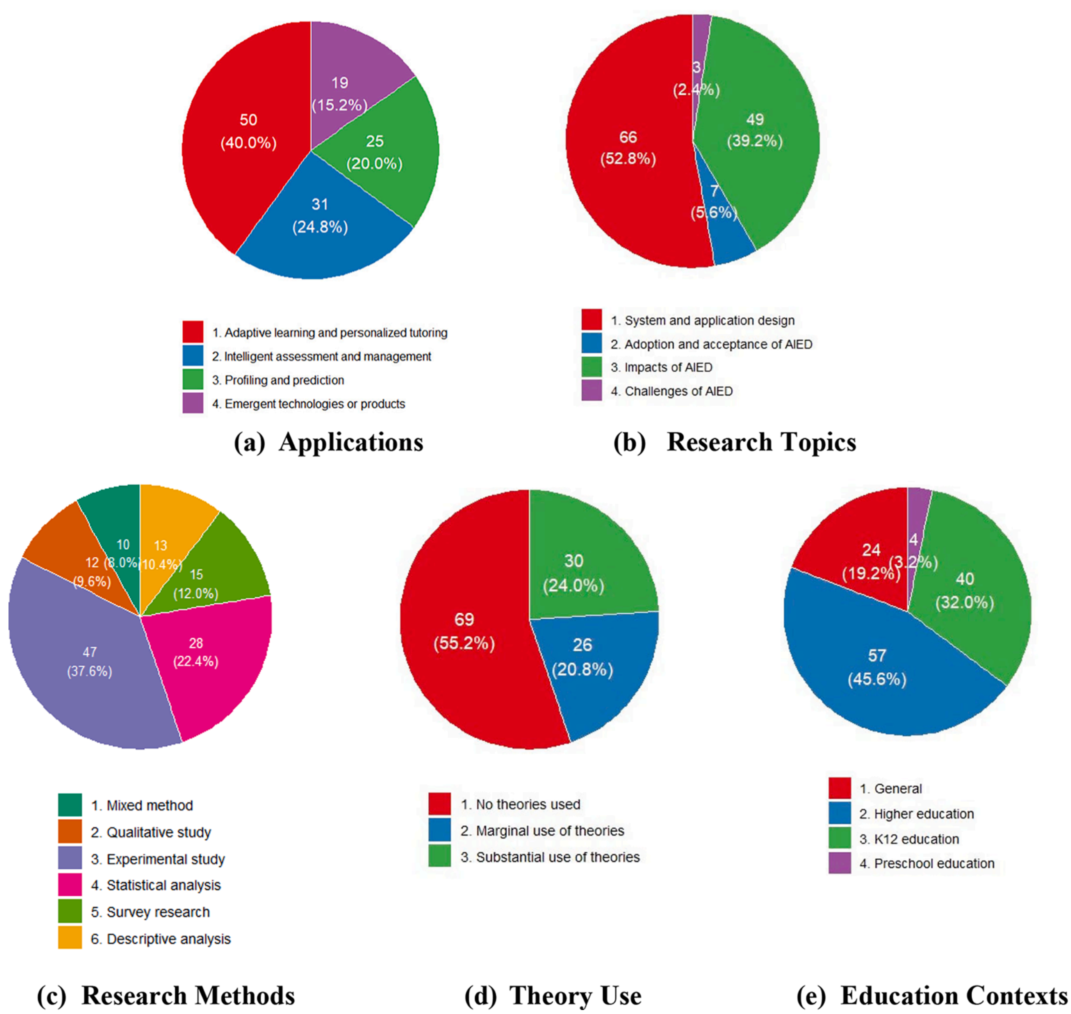


Fig. 9. Distribution of Coding Categories.

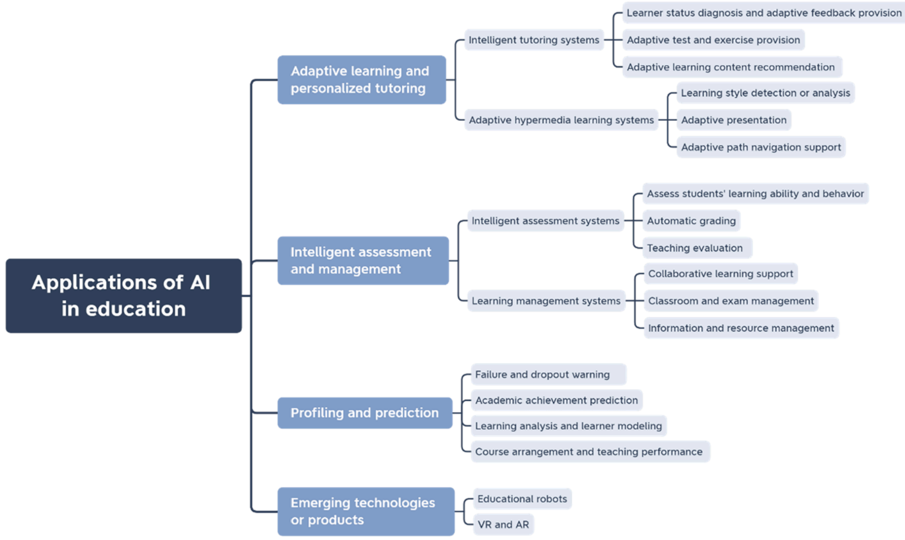


Fig. 10. AIED Applications.

addition, ITS can provide exercises that align with learners' cognitive abilities. Craig et al. (2013) presented a system for mathematics after-school intervention, which dynamically selects exercise content based on students' mastery levels. Beyond tests and exercises, ITS excel at recommending learning materials tailored to learners' status. For instance, they can suggest English reading materials (Hsu et al., 2010) and learning remediation materials (Lin et al., 2016) to minimize students' knowledge disorientation. Due to its versatility and numerous advantages, ITS find applications in various contexts. These include mathematics, chemistry (Rau et al., 2015), sports training (Liu et al., 2021), medical guidance (Poitras et al., 2016), and even animation design teaching (Tang et al., 2022). These diverse applications showcase how ITS enhance learning experiences across a wide range of domains.

Adaptive hypermedia learning systems (AHLS) place a heightened emphasis on accommodating learners' learning styles and preferences, tailoring hypermedia-enabled presentations and navigation support to individual students. This approach positions students at the center of the learning environment. AHLS functions explored in the 16 articles from our sample can be categorized into three primary types: learning style detection or analysis (n = 8), adaptive presentation (n = 4), and adaptive path navigation support (n = 6).

Students exhibit diverse learning styles, including variations like reflective or active learning, field-dependent or independent learning, and intuitive or sensitive learning (García et al., 2007). Applications focusing on learning style detection or analysis frequently employ classification algorithms like Bayesian networks (García et al., 2008; Schiaffino et al., 2008), neural networks (Lo et al., 2012), and decision trees (Lin et al., 2013). These algorithms analyze and identify students' learning styles within an e-learning system, enabling adaptive adjustments to content presentation according to individual preferences. For instance, in the UZWEBMAT system designed by Özyurt et al. (2013), learning objects were tailored in three distinct ways to align with visual–auditory–kinesthetic (VAK) learning styles (Fleming, 2001) for each subject. Lo et al. (2012) crafted an adaptive web-based system featuring an adaptive network interface that aligns with students' cognitive styles.

Additionally, AHLS offer students guidance and navigation assistance to expedite the discovery of learning materials or recommend the most effective learning pathways. These pathways can adhere to the originally planned learning path (Lin et al., 2013) or offer remedial paths for corrective learning (Hsieh et al., 2013). This adaptability empowers students to navigate their learning experiences more effectively.

4.2.1.2. Intelligent assessment and management applications. Tracking and recording students' learning progress and providing timely evaluation are challenging for instructors, particularly in a large class setting. Intelligent assessment and management applications have been developed to address these challenges by offering automatic grading and evaluation capabilities and support for collaborative learning and resource management. As a result, these applications can be categorized into two primary types: intelligent assessment systems and learning management systems.

Intelligent assessment systems (IAS) leverage AI technologies to conduct assessment tasks with high accuracy and efficiency in educational settings. They offer valuable feedback to both students and instructors. Their functions discussed in the 18 articles within our sample can be categorized into three primary types: assessing students' learning abilities and behaviors (n = 9), automatic grading (n = 7), and teaching evaluation (n = 2).

The student assessment function encompasses various elements, including gauging students' knowledge levels (Cheng et al., 2022), assessing their overall competencies (Niu, 2022), and evaluating their learning attitudes (Chen et al., 2007). Student assessment can aid learners in adjusting their learning strategies to enhance their learning outcomes. It can also assist educators in tailoring their teaching methods to suit students' aptitudes. The automatic grading function is fast evolving with a growing trend in activities such as oral training and highly creative writing. For instance, Fu et al. (2020) utilized AI-based digital automatic scoring tools to provide learners with real-time scores and pronunciation corrections, offering immediate feedback. Wilson et al. (2021) investigated an automated writing evaluation system called MI Write, which assesses students' writing quality across six dimensions, including critical thinking development, style, and other personalized traits. The teaching evaluation function employs data mining technology to analyze students' classroom evaluation questionnaires (Agaoglu, 2016).

Learning management systems (LMS) play a crucial role in facilitating teaching management tasks, such as delivering learning resources to students, overseeing and enhancing learner interactions, and streamlining course administrative workflows (Şahin & Yurdugül, 2022). Some LMS platforms also support the responsibilities of school administrators. As a central management platform, LMS serves as a hub connecting instructors, students, and administrators, aggregating substantial volumes of activity data. AI is increasingly integrated into LMS design to enable adaptive and intelligent management of learning and teaching activities. The functions of LMS studied in the 13 articles within our sample can be grouped into three primary categories: collaborative learning support (n = 5), classroom and exam management (n = 4), and information and resource management (n = 4).

The collaborative learning support function in LMS encompasses two distinct types: promoting collaborative writing through document visualization (Calvo et al., 2011) and facilitating remote group discussions (Chen & Tsao, 2021). In remote group discussions, instructors can assign specific roles to students, monitor their participation and collaboration, and receive alerts in case of conflicts among students, allowing timely intervention (Casamayor et al., 2009). The classroom and exam management function relies on the integration of various technologies to enhance classroom teaching. This includes features such as conducting remotely controlled experiments (Kong et al., 2009), providing online examinations (Tasci et al., 2014), delivering real-time automated notifications on student performance in multi-tabletop enabled classrooms (Martinez-Maldonado et al., 2015), and automatically detecting students' focus and attention in classroom settings (Chiu & Tseng, 2021). The information and resource management function supports the exchange of educational materials between instructors and students (Lin et al., 2009), course content management by instructors (Peredo et al., 2011; Yaghmaie & Bahreininejad, 2011), and the recommendation of online courses to students. Recent research proposes integrating virtual assistants into LMS to assist students in navigating course content and providing notifications about various course activities stored in the LMS calendar (Wang & Park, 2021).

4.2.1.3. Profiling and prediction applications. AIED applications focused on profiling and prediction leverage educational data mining and learning analytics to identify learner characteristics, forecast their learning outcomes, empower learners with greater control over their education, and enable educators to identify and assist at-risk students, thereby reducing the likelihood of academic failure (López-Zambrano et al., 2021). Depending on their predictive objectives, functions of profiling and prediction applications in the 19 relevant articles within our sample can be categorized into four types: failure and dropout warning (n = 6), academic achievement prediction (n = 5), learning analysis and learner modeling (n = 4), and course arrangement and teaching performance (n = 4).

Many profiling and prediction applications rely on learner models, which gather and analyze learners' behavioral data to offer effective cognitive and management support. Various methods, such as support vector machines, decision trees, neural networks, and naive Bayes models (Winkler et al., 2021), are employed to build learner models and generate predictions regarding their performance, typically of a quantitative nature. Nabizadeh et al. (2022) discussed AI applications that not only deliver prediction results but also aid course instructors in identifying student types early in the course, enabling them to provide more effective learning support. Furthermore, profiling and prediction applications are designed to predict students' course selections (Kardan et al., 2013) and curriculum satisfaction (Guo, 2010), offering support for curriculum planning and teaching optimization.

4.2.1.4. Emerging products. In addition to the aforementioned categories of AI applications, several emerging products that heavily rely on AI have been discussed and studied. The literature highlights two major sub-categories: (1) educational robots and (2) virtual reality (VR) and augmented reality (AR) applications. These emerging applications enhance the interaction between learners and learning environments or resources, primarily within the context of online education (Du et al., 2023).

Educational robots explored in the literature primarily revolve around chatbots. A chatbot is software that combines AI and natural language processing to interact with a human user through text or voice (Pérez et al., 2020). In the field of education, the use of chatbots varies depending on the capabilities of AI technology and the specific instructional requirements of particular scenarios. Currently, educational chatbots serve primarily four functions: (a) classroom teachers, (b) peer support, (c) companions to foster emotional connections, and (d) telepresence robot teachers (Sharkey, 2016). For instance, Chen et al. (2021) investigated a game-based intelligent robot designed for teaching Chinese idioms. This robot utilizes sound effects and engaging visuals to pique children's interest in learning content. Furthermore, educational robots serve as conversational agents for language conversation exercises (Zhang & Han, 2021) or engage in book discussions with students (Liu et al., 2022), promoting learner autonomy through personalized methods. A study evaluating instructional functions and effectiveness of chatbots identified three key advantages of integrating chatbots into teaching: enhanced interaction with students, increased feedback for students, and user-friendliness (Vázquez-Cano et al., 2021). However, some studies also suggest that while chatbots can yield useful effects, maintaining long-term student interests and engagement is still challenging (Fryer et al., 2017).

VR and AR are cutting-edge immersive technologies that seamlessly integrate the virtual world and the real world in real time, offering users experiences that the physical world alone cannot provide. Of these technologies, AR has gained significant popularity in educational contexts. Out of the 12 relevant articles in our sample, 8 focused on AR applications in education. For instance, Chen et al. (2022) proposed a children's digital art ability training system with artificial intelligence-assisted learning for contour recognition, tone color matching, and color ratio calculation. Students can use smart glasses to view AR paintings, enhancing their imagination and painting capabilities. Lin et al. (2021) examined the influence of AR-enabled AI of Things (AIoT) learning on computational thinking skills training, concluding that AIoT learning can increase students' motivation to learn and has a positive impact on their problem-solving and comprehension. In addition, four articles in our sample explored VR applications in various educational contexts, including art education (Rong et al., 2022) and 360-degree content presentation (Kim et al., 2022). The findings from these studies confirm that AI-supported virtual learning modes are engaging and appealing to students.

4.2.2. Research topics

We identified four main categories of research topics within our sample of AIED studies: system and application design, adoption and acceptance of AIED, impacts of AIED, and challenges of AIED. Fig. 9b illustrates the distribution of these research topics. System and application design emerges as the most frequently studied topic, accounting for 52.8 % of the sample, followed by impacts of AIED at 39.2 %. Adoption and acceptance of AIED represent a small proportion at 5.6 %, while challenges of AIED make up 2.4 % of the sample.

4.2.2.1. System and application design. This stream of research focuses on designing AI algorithms, analytical models, or frameworks, as well as intelligent systems for learning support and learning analytics. Some studies are dedicated to designing and comparing the effectiveness of various machine learning algorithms for mining and predicting students' learning behavior, learning styles, and performance (Costa et al., 2017; Waheed et al., 2020). Other studies revolve around the development and testing of AI-based teaching support systems and auxiliary products, such as cloud collaborative writing support tools (Calvo et al., 2011), interactive intelligent physics teaching systems (Myneni et al., 2013), and trainer systems (Liu et al., 2021). The design and validation of AI models, frameworks, or systems are fundamental to the field of AIED; consequently, this represents the largest category of research topics.

4.2.2.2. Adoption and acceptance of AIED. This stream of research studies factors that influence the adoption and acceptance of AIED applications by instructors as well as by learners. From the instructors' perspective, Wang et al. (2020) identified relative advantage, compatibility, perceived trust, and experience as the determinants of teachers' willingness to adopt ITS. From the learner's perspective, it is reported that system quality, service quality, content quality, technical infrastructure, perceived usefulness, and perceived ease of use are key drivers for adoption (Kreijns et al., 2007; Song & Kong, 2017).

4.2.2.3. Impacts of AIED. This stream of research investigates the impact of AIED applications on various aspects of learning, including academic performance, affective perception, learning behavior, and learning ability. Several studies have highlighted the significant positive impact of AI technology on students' academic performance. For example, research by (Wang, 2014) found that evaluation-centered e-learning systems were effective in promoting students' academic performance and correcting misconceptions, especially for students with low levels of prior knowledge. Moreover, students have demonstrated positive attitudes toward the incorporation of AI into education (Özyurt et al., 2013), expressing increased interest in learning (Liu et al., 2022) and improved concentration (Rong et al., 2022) owing to these applications.

4.2.2.4. Challenges of AIED. This research stream delves into the ongoing issues and challenges in AIED, emphasizing a balanced, social-technical perspective. Several papers in this category discuss a range of challenges related to AIED development. For instance, Maghsudi et al. (2021) highlighted issues encompassing technical aspects (e.g., content production and recommendation), personal aspects (e.g., lifelong learning, assessment and evaluation, incentives, and motivations), and social aspects (e.g., learning networks and diversity and fairness of algorithms) in the development of AIED. Perrotta and Selwyn (2020) focused on the challenges related to the application of deep learning in education, including concerns about data quality, the reductionist approach of deep learning-based applications, and the integration of educational knowledge in application development. Luckin et al. (2016) advocated the importance of building inter-stakeholder partnerships between AI developers, educators, and researchers to develop effective AIED applications. These papers advocate placing humans at the center of application development and considering stakeholders' motivations, involvement, and expertise to address the challenges and ensure meaningful and impactful AIED solutions.

4.2.3. Research methodology

Six research methods are coded, including experiments (37.6 % of the articles in our sample), statistical analysis (including econometric analysis and machine learning model training; 22.4 %), survey research (12 %), descriptive analysis (i.e., with simple illustrative examples; 10.4 %), qualitative studies (9.6 %), and mixed research methods (8 %). Their occurrence distribution is illustrated in Fig. 9c. Among these methods, experiments are the most frequently used and qualitative research is less used. Nonetheless, qualitative research, such as case studies, plays a crucial role in theory building. Enriching qualitative research offers valuable opportunities to gain novel insights and develop useful theories that can significantly contribute to the development and applications of AIED.

4.2.4. Guiding theories

The AIED literature draws upon a diverse set of theories from various fields to inform its research and development. Table 3 summarizes a total of 45 theories coded in our subsample of 125 articles. These theories originate from the fields of psychology (17), education (15), mathematics (6), psychometrics (2), sociology (2), design science (2), and communication (1). The AIED field heavily builds upon psychology and education theories for research development.

Among these theories, the most applied in the literature are constructivist learning theory (6 articles in our sample), learning style theory (6), cognitive theories of learning (5), and item response theory (5). These theories are reviewed in the following.

Table 3
Guiding Theories.

Category	Theories	Count
Education	Constructivist learning theory	6
	Learning style theory	6
	Cognitive theories of learning	5
	The theory of multimedia learning	3
	Self-regulated learning theory	2
	Bloom's taxonomy of cognitive domain	1
	Kolb's experiential learning	1
	Learning-by-doing theory	1
	Reinforcement learning theory	1
	Scaffolding theory	1
	Situational learning theory	1
	The text comprehension theory	1
	The theory of cognitive knowledge acquisition	1
	Tinto's theory of student integration	1
	Zone of proximal development theory	1
Mathematics	Game theory	2
	The knowledge space theory	2
	Fuzzy logic theory	1
	Fuzzy set theory	1
	Graph theory	1
	The mathematical problem-solving theory of Mayer	1
Psychology	Cognitive load theory	3
	Achievement goal theory	2
	Activity theory	2
	Flow theory	2
	Meta-cognition theory	2
	Self-determination theory	2
	The self-efficacy theory	2
	Appraisal theory	1
	Human plausible reasoning theory	1
	Multiple intelligences theory	1
	Social learning theory	1
	Sociocultural theory	1
	The investment theory of creativity	1
	The personal construct theory	1
	The schema theory	1
	The systems model of creativity	1
	Theory of reasoned action	1
Psychometric	Item response theory	5
	Classical testing theories	2
Sociology	Discourse theory	1
	Innovation diffusion theory	1
Design science/ engineering design	Affordance theory	1
	Structure-behavior-function theory	1
Communication	The dialogue theory for critical thinking	1

Constructivist learning theory views learning as an active process of knowledge construction, emphasizing the role of learners in actively shaping their understanding of the world through direct experiences and reflective practices (Bada, 2015; Piaget, 1964). This theory can guide the understanding of the mechanism of AI-simulated or AI-enabled learning. For instance, Winkler et al. (2021) applied the constructivist learning paradigm to investigate whether interactions with scaffolding-based smart personal assistant technology empower students to internalize and independently apply problem-solving strategies. Similarly, Rong (2022) employs constructivist learning theory and reinforcement learning theory to elucidate the impact of AI and VR technology on students' levels of concentration and creativity.

Learning style theory emphasizes the significance of individuals' learning styles and preferences, which shape how they "absorb, process, and retain new information and skills" (Dantas & Cunha, 2020, p. 1). This theory encompasses a wide array of concepts and models aimed at elucidating the variations in learners' preference to learn. Some notable models include Kolb's learning styles inventory (Kolb, 1976), Felder and Silverman's learning style model (Felder, 1988), Honey and Mumford's learning style model and learning styles questionnaire (Honey & Mumford, 1986), and Fleming's VAK learning style model (Fleming, 2001). Learning style theory particularly pertains to the development of adaptive learning systems. For instance, Özyurt et al. (2013) utilized the VAK learning style model to tailor learning materials within an adaptive and intelligent individualized e-learning environment named UZWEBMAT. García et al. (2008) employed Felder and Silverman's learning style model (Felder, 1988) to identify the learning styles of engineering students in online courses.

Cognitive theories of learning elucidate learners' behaviors through the lens of their mental processes. For example, Mednick (1962) theory of creativity addresses the cognitive aspects of creativity, positing that creativity arises from an individual's ability to synthesize various elements or ideas in novel and imaginative ways. Piaget's theory of cognitive development (Piaget, 1936, 1971), another prominent example, posits four stages in the construction of a mental model of the world: sensorimotor, preoperational, concrete operational, and formal operational stages. Within the field of AIED, cognitive theories often serve as foundational frameworks for ITS research and other related studies (Aleven et al., 2009; Waalkens et al., 2013).

Item response theory originates from psychometric research and is "a psychometric technique used in the development, evaluation, improvement, and scoring of multi-item scales" (Toland, 2013, p. 120). It provides a framework for assessing learners' abilities, attitudes, or unobservable characteristics based on their responses to observable items, such as test items (Carlson & Davier, 2013), which are commonly adopted in AIED applications (Yang & Li, 2018). Such assessments of student mastery level in learning is essential for the development of systems like personalized education (Maghsudi et al., 2021), intelligent assessment systems (Csapó & Molnár, 2019), and adaptive learning systems (Yang et al., 2013).

In summary, AIED research applies a wide range of theories, reflecting its interdisciplinary nature. This diversity in theory application mirrors the multifaceted nature of AIED research and its evolving landscape of topics. Furthermore, the literature demonstrates varying degrees of theory application. Fig. 9d illustrates that approximately 24 % of articles use one or more primary theories to systematically guide the research design (e.g., developing research framework or hypotheses), while 20.8 % of articles use theories marginally (e.g., referencing theories without much elaboration or in the explanations of the research results). The remaining articles (55.2 %) do not prominently feature theories in their discussions.

4.3. Research context: Education stages

For use contexts, AIED research spans various stages of the educational process: higher education, K12 education, preschool education, or general education (without specifying a particular stage). Fig. 9e illustrates the distribution of these education stages within the 125 papers we reviewed. Approximately half of the research (45.6 %) centers on higher education, followed by K12 education (32 %) and general education (19.2 %). Preschool education garners the least attention (3.2 %). This discrepancy may stem from the perception that AI-supported education is better suited for adult learners who are more autonomous and self-regulated, while preschool education requires greater human care and attention. It also offers significant opportunities for AIED research.

5. Discussion

This research employs bibliometric analysis and content analysis for a systematic review of the AIED literature. In the bibliometric analysis, the keywords co-occurrence analysis reveals two sets of concept clusters explored in the literature. The keywords plus co-occurrence network highlights four concept clusters: user behaviors, design science, big data analytics, and AIED impacts. Conversely, the author keywords co-occurrence network illustrates concept clusters related to machine learning, educational technology, intelligent systems, emerging technologies, and AI education. A detailed examination uncovers both similarities and disparities between these two sets of clusters. The clusters derived from author keywords offer a more detailed perspective than those identified in the keywords plus network. For instance, the educational technology, learning systems, and emerging technologies clusters within the author keywords network correspond to the design science cluster in the keywords plus network. However, it's noteworthy that the AIED user behavior cluster identified in the keywords plus network does not appear in the author keywords network.

The subsequent content analysis provides insights into various research elements, including research objects (i.e., AIED applications), research objectives and topics, research methods, guiding theories, and research contexts (i.e., education stages). The literature explored four primary categories of AIED applications, including adaptive learning and personalized tutoring, profiling and prediction, intelligent assessment and management, and emerging products, with adaptive learning and personalized tutoring being the most extensively studied. Among the four research topics identified (i.e., system and application design, adoption and acceptance of AIED, impacts of AIED, and challenges of AIED), system and application design emerged as the most frequently investigated. Experiments prove to be the predominant research method among the five categorized research methods, which include mixed research methods, qualitative studies, experiments, statistical analysis of secondary data, survey research, and descriptive studies. Among the 45 theories identified from the literature, constructivist learning theory, learning style theory, and cognitive theories of learning are the most commonly employed theories guiding or supporting the theoretical development of research. Higher education and K12 education are the top two research contexts that receive significant attention in the AIED literature.

This research contributes to the AIED literature in several ways. First, it adds to the body of AIED reviews by offering a systematic exploration of the literature's conceptual structure. While prior reviews have explored the general AIED research field or specific domains AIED applications (Chassignol et al., 2018; Goksel & Bozkurt, 2019; Guan et al., 2020; Hwang et al., 2020; Srinivasan, 2022), few have systematically examined the conceptual underpinnings of the literature. In this study, we employ both bibliometric analysis and content analysis to unveil the concepts associated with research elements of central interest to scholars. This approach yields a comprehensive understanding of the literature, going beyond the exploration of research objects and AIED applications to include guiding theories, research topics, and research methodologies. Their occurrence distributions summarized in Fig. 9 inform the current status of the research design elements.

Second, the study enriches our comprehension of the AIED research landscape and spotlights several areas for research attention. For instance, there are clear opportunities for research on the integration of the latest advancements in AI technologies. While our review encompasses a broad spectrum of AIED applications, certain latest developments, such as generative AI, are absent from our sample articles. Generative AI benefits from substantial human involvement for superior results, making it a promising domain for scholarly exploration. Recent research in AIED has increasingly emphasized the role of humans in AI application design, with a shift toward paradigms that emphasize learner collaboration and leadership (Andersen et al., 2022; Ouyang & Jiao, 2021; Xu & Ouyang, 2022). Developing AI systems for learners in leadership roles remains an ongoing and intricate task (Ouyang & Jiao, 2021), and generative AI offers the potential to assist and engage users, as either leaders or collaborators, in task completion.

Another area deserving of attention is AI in preschool education, which is underrepresented in our sample. AI applications in preschool education may necessitate more engaging design and greater involvement of parents. Designing applications that are captivating for both parents and children presents a promising avenue for exploration. User emotion is another area offering prosperous opportunities for further research. While emotions are crucial to learning in IT-driven environment (Li et al., 2023), existing AIED applications are mostly weak AI with limited ability for emotional connections with users. Consequently, studies on user emotion are lacking in our sample. Future research can systematically study user emotions and their roles in the AI-empowered learning environment. For example, flow theory (Csikszentmihalyi, 1990) stands out as a promising theoretical framework to guide future research on AIED applications for preschool educations. Flow represents a state of heightened focus, concentration, and enjoyment. AIED system designs that stimulate a state of flow can exert a long-lasting impact on learning.

Additionally, ethical considerations are another important field of future study. In our review, AIED ethical studies did not emerge as a major research theme in the keyword co-occurrence analysis and content analysis. However, some ethics concerns have been generally discussed in "challenges of AIED". The increasing integration of AI technologies in education has led to growing ethical risks and concerns, including issues related to personal data privacy, algorithm biases, and learner and educator autonomy (Akgun & Greenhow, 2022; Boulay, 2023; Wells, 2023). For example, learning analytics may incentivize aggressive collection of personal and surveillance data, students may learn biased knowledge from ChatGPT or other AI models, and teachers may develop reliance on analytics results to make decisions on students who are in difficulty and require additional assistance (Boulay, 2023). Biased algorithms can also perpetuate problematic social values. For example, it is recognized that AI-driven language translation tools routinely introduce gender stereotypes when translating from gender-neutral languages, thereby influencing language learners' social perceptions regarding gender (Miller et al., 2018). Therefore, designing AIED applications that adhere to ethical standards is vital for the well-being of humanity. Future research can expand to include topics such as the ramifications of ethical risks, users' perception of AIED ethical risks, and how such perceptions affect their behaviors regarding the adoption and usage of AIED applications. Design science researchers can incorporate ethical criteria as one of the performance metrics in their experiment design—criteria for evaluating AIED applications encompass not only learning effectiveness and algorithm accuracy but also fairness, algorithm transparency, and trust.

The analysis of research methodologies highlights opportunities for developing high-quality research. Notably, mixed research methods, which have the potential to significantly enhance result robustness and, consequently, research quality, are underutilized in the field. Moreover, over half of the empirical studies in the AIED field do not integrate any theoretical frameworks into their research development. Future research endeavors can strive for more rigorous research designs and methodologies to further enhance the overall quality of research in the domain. For instance, design science research in AIED can benefit from the application of design theories such as affordance theory. These theories can systematically guide scholars and developers in identifying and designing functionalities to achieve important affordances for AIED (Crompton et al., 2022; Wang et al., 2024).

This research underscores the importance of qualitative studies for the advancement of the AIED research field. As the existing research has primarily focused on AIED application development and empirical studies (Ågerfalk & Karlsson, 2020), qualitative research methods, which are instrumental for theory generation, are underrepresented. However, in the age of AI, a plethora of foundational questions resurface, demanding fresh perspectives and answers. These questions encompass topics like potential disparities in learning styles in the era of AI, the evolving nature of teaching in the presence of AI, the development of design science in AIED (Goldkuhl & Sjöström, 2021), and the exploration of digital experiences for learners and other stakeholders (Kreps, 2021). Addressing these questions through qualitative studies, such as case studies and expert panel interviews, can lead to novel theoretical frameworks and innovative insights, thereby contributing to the academic advancement of AIED (Myers, 2009; Yin, 2009).

Our research highlights the cross-disciplinary nature of the AIED research. Through a granular analysis of the top 15 cited references, we identified Computer Science and AI, MIS, and Education as three major disciplines foundational to AIED research. Additionally, the summarized theories suggest that education and psychology serve as two primary disciplinary categories. Consequently, fostering increased collaboration among computer scientists, psychologists, educators, and MIS experts is a viable path towards higher calibre and more innovative AIED research. For example, scholars from psychology and education can provide theoretical guidance for research design, while computer scientists can bring their programming expertise to research collaboration. Moreover, successful interdisciplinary collaboration requires integrative contributions from multiple disciplines and overcoming functional silos (Turner & Baker, 2020). MIS scholars can play an important role in facilitating such integration, given that MIS is inherently a cross-disciplinary field and its scholars often possess experience in integrative research.

6. Conclusions

This research employs a mixed research method, combining bibliometric analysis and content analysis, to uncover and comprehend the core concepts within the field of AIED. The findings from both approaches converge, providing a comprehensive understanding of AIED concepts. This study contributes to the body of AIED literature reviews by emphasizing the importance of grasping the conceptual structure of the field. Additionally, the research suggests several future directions, including the need to incorporate latest AI technologies, strengthen AIED research in the preschool education context, enhance research quality through mixed methods, prioritize theoretical contributions and enhance collaboration among computer scientists, psychologists, educators, and MIS experts.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix:. Impactful papers

1a. Top Globally Cited Papers.

1 García, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education*, *49*(3), 794–808.

2 Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N. (2020). Impact of COVID-19 Pandemic on Information Management Research and Practice: Transforming Education, Work and Life. *International Journal of Information Management 55*, Article 102211.

3 Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*(39), 1–27.

4 Costa, E. B., Fonseca, B., Santana, M. A., Araújo, F. F. d., & Rego, J. (2017). Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses. *Computers in Human Behavior*, *73*, 247–256.

5 Chou, C.-Y., Chan, T.-W., & Lin, C.-J. (2003). Redefining the learning companion: The past, present, and future of educational agents. *Computers & Education 40*(3), 255–269.

6 Santos, D. P. d., Giese, D., Brodehl, S., Chon, S. H., Staab, W., Kleinert, R., Maintz, D., & Baeßler, B. (2019). Medical students' attitude towards artificial intelligence: A multicentre survey. *European Radiology 29*, 1640–1646

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14 Custers, E. J. F. M. (2015). Thirty years of illness scripts: Theoretical origins and practical applications. *Medical Teacher*, *37*(5), 457–462.

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1b. Top Locally Cited Papers.

1 García, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education*, *49*(3), 794–808.

2 Santos, D. P. d., Giese, D., Brodehl, S., Chon, S. H., Staab, W., Kleinert, R., Maintz, D., & Baeßler, B. (2019). Medical students' attitude towards artificial intelligence: A multicentre survey. *European Radiology 29*, 1640–1646.

3 Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial intelligence trends in education: A narrative overview. *Procedia Computer Science 136*, 16–24.

4 Hinojo-Lucena, F.-J., Aznar-Díaz, I., Cáceres-Reche, M.-P., & Romero-Rodríguez, J.-M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Science*, *9*(51), 1–9.

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1c. Top 15 Cited References.

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Note: Star (*) indicates papers from disciplines other than the research field of AI in education.

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