Computers and Education: Artificial Intelligence 9 (2025) 100513

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence

Mapping the evolution of AI in education: Toward a co-adaptive and human-centered paradigm

Shihui Feng [a], Huilin Zhang [a], Dragan Gašević [b,*]

[a] Unit of Mathematics, Science, and Technology, Faculty of Education, University of Hong Kong, Hong Kong, China
[b] Department of Human Centred Computing, Monash University, Australia

ARTICLE INFO

Keywords:
AIED
Generative AI
Human-AI collaboration
Large language models
Multimodal learning analytics
Keyword co-occurrence networks

ABSTRACT

This study analyzes 2398 research articles published between 2020 and 2024 across eight core venues related to the field of Artificial Intelligence in Education (AIED). Using a three-level knowledge co-occurrence network analysis, this study analyzes the knowledge structure of the field, the evolving knowledge clusters, and the emerging frontiers. The findings reveal that AIED research is centered on developing AI-assisted systems and using AI to support educational analysis, with sustained themes such as intelligent tutoring systems, learning analytics, and natural language processing, alongside rising interest in large language models (LLMs) and generative artificial intelligence (GenAI). By tracking the bridging keywords over the past five years, this study identifies four emerging frontiers in AIED, including *LLMs, GenAI, multimodal learning analytics*, and *human-AI collaboration*. The current research interests in GenAI are centered around GAI-driven personalization, self-regulated learning, feedback, assessment, motivation, and ethics. Our findings underscore the need to consciously shape these technical pursuits through co-adaptive and human-centered principles. It is essential to proactively bridge these advanced technical capabilities with core educational values and purposes to ensure that technological development is guided by educational goals, ethics, and a commitment to human agency and education equity. This study provides a large-scale field-level mapping of AIED's transformation in the GenAI era and sheds light on the future research development and educational practices.

1. Introduction

The field of Artificial Intelligence in Education (AIED) is undergoing a rapid development, driven by the advances of generative artificial intelligence (GenAI) and large language models (LLMs). This shift moves the field's focus from systems that assess and guide learning to those that can generate educational content and interactions (Allison et al., 2025; Aryadoust et al., 2024). While this promises unprecedented scalability and personalization, it also intensifies core, pre-existing tensions within the field. Key challenges include the risk of prioritizing technological capability over pedagogical soundness (Gašević et al., 2015; Mustafa et al., 2024; Topali et al., 2025), the potential for AI to undermine learner agency and metacognition (Fan et al., 2025), and the threat of exacerbating educational inequalities through algorithmic bias and the digital divide (Ali et al., 2024; Allison et al., 2025; Feng & Tan, 2024; Pedro et al., 2019). Navigating this new paradigm requires a clear-eyed understanding of the field's current focus and emerging development trajectories.

The current reviews and analyses have provided valuable qualitative syntheses of AI applications in education (Chiu et al., 2023; Garzón et al., 2025; Matos et al., 2025; Mustafa et al., 2024). However, as AIED is inherently interdisciplinary, drawing from computer science and learning sciences, a comprehensive understanding requires a macroscopic view. There is a lack of a systematic mapping of the AIED landscape within the recent GenAI context—one that can identify the field's key foci and emerging frontiers through the quantitative analysis of a large dataset. Our study addresses this gap by adding a large-scale, data-driven perspective that captures the entire research landscape at a system level. This macroscopic and systematic view is a necessary precursor to a more nuanced assessment of the field's direction and the informed prioritization of future research.

To address this gap, the objective of this study was to conduct a systematic, large-scale analysis of the AIED research landscape from 2020 to 2024. This five-year period captures a critical phase, beginning with the release of GPT-3 in 2020 (Brown et al., 2020), which marked a fundamental shift in AI capabilities. Analyzing this specific window

* Corresponding author.
E-mail addresses: shihuife@hku.hk (S. Feng), zhanghuilin0216@gmail.com (H. Zhang), Dragan.Gasevic@monash.edu (D. Gašević).

https://doi.org/10.1016/j.caeai.2025.100513
Received 25 June 2025; Received in revised form 27 October 2025; Accepted 27 November 2025
Available online 2 December 2025

allows us to understand the field's immediate and rapid response to these transformative technologies and its evolution at the onset of the GenAI era. The primary objective of this study was to provide a macro-level, structural map of the AIED field using knowledge co-occurrence network analysis. The purpose was not to pass judgment on the field's direction, but to provide its first comprehensive structural diagnosis in the GenAI era. This study was therefore driven by a central question: What overarching shifts and tensions characterize the recent evolution of AIED, and what are the implications for its future trajectory? This was investigated through the following three specific research questions:

1. What is the knowledge structure of AIED between 2020 and 2024?
2. What are the key knowledge clusters of AIED within this period?
3. What emerging frontiers signal the field's future direction?

This study provides a timely contribution by offering a large-scale, data-driven mapping of the AIED field's transformation during a pivotal five-year period (2020–2024) marked by the rise of large language models and generative AI. By employing a three-level knowledge co-occurrence network analysis of 2398 articles, this study uncovers the foci and the emerging frontiers of AIED research in the GenAI era. The findings serve as a critical reference for researchers, practitioners, and policymakers, providing the data-informed evidence needed to ground future critical debates and inform strategic research funding. Furthermore, the identification of human-AI collaboration as a key emerging trend underscores the growing importance of a human-centered paradigm for the future of AI in education.

2. Related work

With the ongoing expansion of AIED research, comprehensive reviews are needed for elucidating the key topics in the field and offering directions for future studies. First, thematic reviews have synthesized research topics through systematic analysis and content analysis (Garzón et al., 2025; Matos et al., 2025). For instance, Zhang and Aslan (2021) aimed to map the AIED research field by analyzing 40 empirical studies on AI in education published between 1993 and 2020. They identified core topics such as chatbots, expert systems, intelligent tutors and agents, machine learning, and personalized learning systems and environments. Similarly, Mustafa et al. (2024) reviewed the AIED field by examining 143 articles using the technology-enhanced learning model as a coding framework. Their results indicated that AI applications in education predominantly focus on higher education, teacher support, and student learning, while receiving comparatively limited attention in areas such as administration, school leadership, and special education. Chen et al. (2020) aimed to review the applications of AI in administration, instruction, and learning. They analyzed 250 highly cited articles, and identified a number of emerging directions, including affective detection in game-based learning, the integration of machine learning with adaptive learning systems, teacher response tools, the use of AI techniques in dialogue analysis, and support for individuals with intellectual disabilities. Likewise, Zhai et al. (2021) aimed to map the applications of AI in education and to identify its emerging research trends and challenges. They analyzed 100 AIED publications from 2010 to 2020, proposed four critical avenues for future research: the Internet of Things, collective intelligence, deep learning and neurocomputation, and assessment systems. While these studies provide valuable theoretical references, the inherent interdisciplinarity and topic diversity of AIED necessitate a large-scale, quantitative approach to reliably map its complex knowledge structure and emerging frontiers.

Second, application- and domain-specific reviews have provided valuable depth on the implementation of AI in contexts like medical education, STEM, and language learning (e.g., Lifshits & Rosenberg, 2024; Q. Wang et al., 2025; Y. Wang & Xue, 2024; Wu & Wang, 2025; W. Xu & Ouyang, 2022). These studies effectively showcase how AI tools can enhance engagement and higher-order thinking in specific domains (Z. Li, Lee, & Botelho, 2024; Q. Wang et al., 2025). However, by their nature, these focused reviews offer a fragmented view of the field. They illuminate individual trees—the specific tools, ethical frameworks (An et al., 2024), and meta-analytical impacts (Alemdag, 2025)—but cannot reveal the architecture of the entire forest, namely the macro-level structural relationships and evolutionary pathways that connect these diverse applications.

Third, a growing number of reviews have employed bibliometric methods to provide a more quantitative overview. For example, Delen et al. (2024) visualized publication patterns across a long time span, and Bozkurt et al. (2021) identified key research clusters from a corpus of 276 articles. The study most methodologically aligned with ours is Feng and Law (2021), who proposed a novel keyword co-occurrence network analysis to 1830 articles from 2010 to 2019, providing a foundational data-driven map. However, their analysis concluded just as the generative AI revolution began, and their two-year interval clustering does not capture the rapid, micro-level emergence of new frontiers.

In summary, the current study aimed to addresses three critical gaps: 1) Scope and Timeliness: the study analyzed a large set of 2398 articles published in core venues related to AIED from the pivotal 2020–2024 period to capture the field's transformation in the GenAI era; 2) Methodological Advancement: the study employed a novel, three-level knowledge co-occurrence network analysis to dynamically track the evolution of knowledge clusters and identify emerging frontiers. 3) Systematic Mapping: this study provides a systematic mapping of the knowledge organization of AIED field, to analyze the knowledge structure at the macro-level, the coherent knowledge clusters at the meso-level, and the emerging topics at the micro-level.

3. Method

3.1. Data collection and pre-processing

In this study, all publications from 2020 to 2024 were collected from eight core publication venues related to AIED, including (1) International Conference on Artificial Intelligence in Education (AIEDC); (2) International Journal of Artificial Intelligence in Education (IJAIED); (3) International Conference on Educational Data Mining (EDM); (4) ACM Conference on Learning at Scale (L@S); (5) International Conference on Intelligent Tutoring Systems (ITS); (6) Journal of Learning Analytics (JLA); (7) International Learning Analytics & Knowledge Conference (LAK) proceedings; (8) Computer and Education: Artificial Intelligence (C&EAI). The selection of these eight venues was determined through consultations with leading experts in the field. These eight publication sources comprehensively span the intersection of education and artificial intelligence, with coverage ranging from theoretical exploration to technological innovation and real-world application, aiming to provide a holistic representation of developments in AIED research.

All articles published in these eight sources between 2020 and 2024 were collected to analyze research topics and trends in AIED. Detailed information of each source is provided below:

AIEDC: 484 full and short papers
IJAIED: 256 articles
EDM: 280 full and short papers (not including posters)
L@S: 363 articles
ITS: 269 articles
JLA: 157 articles
LAK: 379 full and short papers
C&EAI: 331 articles

This study maps recent AIED developments through keyword network analysis, which requires rigorous data pre-processing of the retrieved article keywords. This study excluded 112 articles that did not provide any keywords. In the remaining dataset, where the number of keywords ranged from 1 to 28 (Mdn = 5), nine articles (0.3 %) were removed for containing more than 10 keywords. This was done because articles with an unusually high number of keywords often signify a lack of thematic focus, which can obscure their core contribution. This step was taken to enhance the conceptual clarity of the co-occurrence network. After that, we pre-processed the keywords to ensure consistency and eliminate redundancy based on the following steps:

1) *Converting to lowercase and removing hyphens*
2) *Converting plurals into a singular form*—Using the WordNetLemmatizer from Python's Natural Language Toolkit (NLTK), plural keywords were transformed into their base forms. While this process achieves high accuracy, rare errors such as improperly transforming "SES" into "S" still existed and were resolved through manual verification.
3) *Replacing abbreviations with their corresponding full forms*— Abbreviations in the keywords were replaced with their full forms using two different approaches: (a) extracting keywords with parentheses (e.g., "explainable ai (xai)") and removing their abbreviations, and (b) manually verifying keywords with fewer than four characters or written in uppercase to identify abbreviation candidates.
4) *Merging synonyms*—Keywords with identical meanings but different expressions were unified to ensure consistency in representing research content. Synonymous keywords were identified using Python's rapidfuzz library with a similarity threshold of 90, followed by manual validation. Four types of synonym variations were addressed, including (a) different spellings (e.g., "human centered computing" vs. "human centered computing"), (b) typographical errors (e.g., "principle component analysis" vs. "principal component analysis"), (c) compound words and split words (e.g., "clickstream" vs. "click stream"), and (d) semantically equivalent expressions (e.g., "automated assessment" vs. "automatic assessment").

After the data pre-processing, there are 4733 distinct keywords from the 2398 articles in the final dataset for the following analysis.

3.2. Data analysis

This study employed a novel three-step approach of keyword co-occurrence network (KCN) analysis proposed by Feng and Law (2021). The three step-approach provides a comprehensive, multi-level diagnosis of a research field: it uses macro-level network metrics to unpack the global knowledge structure, meso-level community detection to uncover knowledge clusters, and micro-level temporal analysis of betweenness centrality to identify emerging keywords (see Fig. 1). This novel structured, multi-level approach is particularly suited to analyze a complex, interdisciplinary research field like AIED, as it systematically uncovers the field's latent intellectual architecture—revealing its core pillars, its specialized sub-communities, and the emerging concepts that signal its future trajectory.

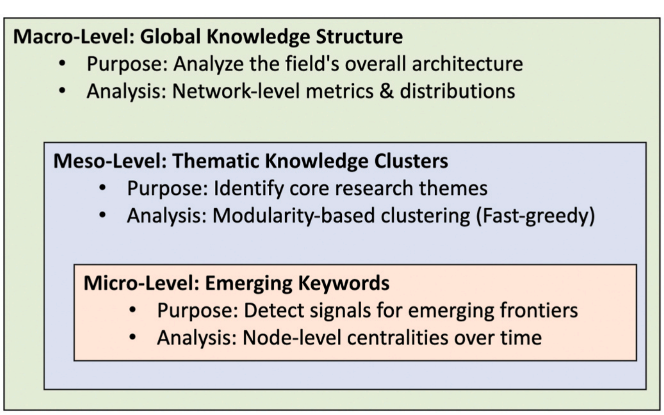

Fig. 1. A framework for the three-level knowledge Co-occurrence network analysis.

A Keyword Co-occurrence Network (KCN) is a weighted graph representation of keyword relationships in academic literature, where nodes correspond to keywords and edges reflect co-occurrence frequencies. Crucially, this means the analysis moves beyond simple word frequency to focus on the structural characteristics and relational dynamics within the network. The network topology of a KCN reveals the knowledge structure of a field, while node-level metrics quantify keyword importance (Radhakrishnan et al., 2017; H. Su & Lee, 2010). KCNs are considered an effective tool for large-scale knowledge mapping within a research field (Radhakrishnan et al., 2017). This study conducted all data analysis using Python, specifically the NetworkX and iGraph packages for network analysis and visualization.

To address RQ1 (macro-level), the structural characteristics of the constructed KCN were analyzed. The analysis began with an examination of the distribution of weighted degrees against a power law distribution to assess whether the network follows a scale-free topology. Next, the analysis focus on the relationship between node degree—the number of connections a keyword (node) had—and its weighted local clustering coefficient—a measure of how densely interconnected a node's neighbors are, weighted by the strength of their associations. This analysis helped determine whether the network exhibited a structure where a small subset of keywords had many sparsely connected associations, while the majority of keywords had fewer but more densely connected associations. Lastly, the tendency of nodes to connect with others of higher or lower degrees was further examined by analyzing the relationship between node degrees and their average weighted nearest neighbor degree. A modified average weighted nearest neighbor degree measure was employed (Feng & Law, 2021), which calculated the average degree of a node's neighbors while accounting for edge weights. The modified version further divided this value by the focal node's degree to assess homophily tendencies at the node level.

To address RQ2 (meso-level), modularity-based clustering identified community structures within the KCNs, revealing cohesive research themes in AIED. Communities (or clusters) are network subgroups where nodes exhibit denser internal connections than external ones, indicating shared characteristics (Fortunato, 2010). In KCNs, keywords clustered together represented distinct knowledge domains within AIED. The fast-greedy algorithm was implemented (Clauset et al., 2004) on each KCN's largest connected component to optimize computational efficiency and reduce noise. This approach automatically determined the optimal number of communities by maximizing modularity—a metric quantifying partition quality by comparing intra-vs. inter-cluster edge density (Newman, 2006). Higher modularity values indicated more meaningful community divisions. The fast-greedy algorithm efficiently handled large networks via hierarchical agglomeration while optimizing global modularity (Clauset et al., 2004), making it ideal for mapping structural shifts in AIED's research landscape over time. Each identified knowledge cluster was named after the keyword with the highest in-group degree. At the meso-level, analysis included both the static knowledge clusters of AIED between 2020 and 2024, and the temporal knowledge clusters of the KCNs for each year to traced knowledge evolution over time.

To address RQ3 (micro-level), the temporal KCNs for each year underwent a micro-level analysis to identify trending and bridging keywords using weighted betweenness centrality. Keywords exhibiting high weighted betweenness centrality act as gatekeepers, bridging disparate keyword clusters and maintaining knowledge connectivity across AIED's research landscape. The nodes showing sudden increases in betweenness centrality were considered new trending topics (Y. Yang et al., 2014).

Furthermore, to provide a deeper understanding of the themes and clusters identified through the KCN analysis, this study incorporated content analysis as a complementary qualitative approach. For each knowledge cluster obtained from modularity-based clustering, articles containing the cluster's core keywords were closely reviewed and summarized, synthesizing their research objectives, methodologies and key findings to elucidate the substantive content within each cluster. For the emerging keywords with high betweenness centrality, literature from the entire database containing these keywords was also retrieved and examined, with attention to their application scenarios, methodological innovations, and primary challenges. This combined approach enriches interpretation of the application features and potential impacts of these concepts within the AIED field, and to outline possible directions for their future development.

4. Results

4.1. Most frequent keywords in AIED field (2020–2024)

The top 20 keywords with the highest frequency in AIED from 2020 to 2024 (the last five years) are shown in Fig. 2. Keywords including machine learning, natural language processing (NLP), LLMs, GenAI, and deep learning feature prominently, underscoring the technical focus of AIED research. Regarding educational implications, the period saw strong interest in concepts including self-regulated learning, assessment, feedback, collaborative learning, and online learning. During the last five years of 2020–2024, AI rapidly rose to become the second most frequent keyword. The emergence and rising prominence of keywords such as LLM, GPT, and GenAI reflect the recent advances in foundational AI technologies and their rapid adoption in educational settings.

4.2. Knowledge structures of the AIED field (2020–2024) (RQ1)

The structural characteristics of the constructed KCN reveal the underlying knowledge structure of the AIED field. Our analysis showed that the KCN exhibited a hierarchical structure, characterized by two key properties: a heavy-tailed degree distribution and a high clustering coefficient (Ravasz & Barabási, 2003). This structure suggests that a small subset of keywords dominated the literature, while the majority appear only sporadically.

Table 1 provides a summary of the structural features of the temporal and overall KCNs. The network metrics provide insights into the evolving connectivity and thematic organization of AIED research. The yearly KCNs consistently showed low density (sparse connections) but high local clustering (local keyword groupings). The average degree (z) and average strength (s) showed a fluctuating upward trend over the past five years, reaching their peak in 2024. This indicates that both the breadth and the intensity of connections among research topics have further increased in recent years. The largest component (lc) refers to the maximal subset of nodes in a network in which every pair of nodes can be reached via paths. The high *lc* values approaching the total number of nodes (*n*) in each year indicates strong interconnectedness among keywords within AIED. Overall, in the past five years, the proportion of the largest component to the total number of nodes has reached 95 %, with annual proportions ranging from 82.9 % to 93.1 %. This demonstrates that there were extensive connections and interactions among research topics within the field of AIED. The degree correlation coefficient (r) of the network was negative, indicating a certain level of disassortativity; that is, nodes with high degrees tended to connect with those with low degrees. This pattern likely arised because mainstream topics (eg. 'natural language processing', 'artificial intelligence') served as "hubs" within the network, frequently co-occurring with a range of specialized or emerging topics.

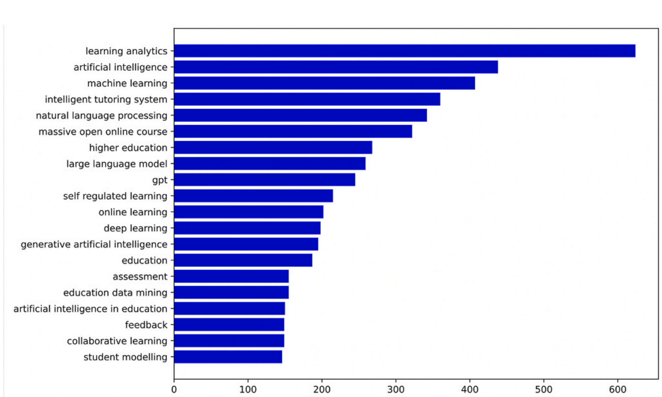

Fig. 2. Top 20 keywords with the highest frequency.

The weighted degree distribution of the KCN exhibited a power-law distribution, as shown in Fig. 3. The vast majority of nodes had low weighted degrees and were connected to only a few other nodes, while only a small number of hub nodes possessed extremely high weighted degrees and accounted for a large proportion of the network's connections. In this study, the fitted power-law exponent was 2.28. As noted by Newman (2003), power-law exponents for networks typically fall within the interval between 2 and 3, and the result of the overall KCN was consistent with this empirical regularity.

Fig. 4 illustrates the relationship between node degree and the weighted clustering coefficient in the KCN. As node degree increased, the weighted clustering coefficient declined markedly, reflecting a significant negative correlation between these two metrics. This trend suggests that high-degree nodes, although connected to numerous neighbors, were characterized by a relatively low likelihood of interconnections among their neighbors, resulting in sparser neighborhood structures and weaker local clustering. Conversely, the limited neighbors of low-degree nodes were more likely to form densely interconnected groups, thus exhibiting higher weighted clustering coefficients and indicating more cohesive local structures.

The relationship between the weighted average nearest neighbor degree and node degree is shown in Fig. 5. The red dashed line represents the reference line where the ratio equals 1, serving as a threshold to distinguish the association tendencies of nodes. It can be seen that most nodes in the network tended to be connected with nodes of higher degree. As the node degree increased, the ratio of the weighted average nearest neighbor degree to the node's own degree generally showed a decreasing trend. This indicates that nodes with higher degrees were more likely to connect with nodes of lower degree.

4.3. Knowledge clusters of the AIED field (2020–2024) (RQ2)

Frequency analysis alone cannot capture the relationships among keywords. Therefore, construction of a KCN with the 4733 distinct keywords from the 2398 articles published between 2020 and 2024 and conducted the meso-level analysis to identify the knowledge clusters of the AIED field. This study also constructed a temporal KCN for each year and analyzed the knowledge clusters of each temporal network to present the developmental trajectory of the field.

Fig. 6 below presents the network visualization of the knowledge clusters of AIED research from 2020 to 2024, with the top ten largest knowledge clusters labelled in the graph. The **most prominent knowledge clusters** over the last five years were 'natural language processing', "learning analytics', massive open online courses', 'artificial intelligence', 'engagement', 'intelligent tutorial system', 'causal inference', 'lifelong learning', 'computer vision', and 'data science application in education'. A table in appendix shows the top 10 highest in-group degree keywords for each knowledge cluster. These keywords represent the most central and frequently co-occurring terms within each cluster and support the interpretation of each knowledge cluster.

It is noteworthy that Fig. 6 shows numerous interconnections of varying thickness among the knowledge clusters, reflecting both knowledge exchange and interdisciplinary integration within the field. The thicker links between clusters such as 'natural language processing',

Table 1
Structural Characteristics of the keyword co-occurrence networks.

	n	m	d	c	z	s	lc	r
2020	1270	3519	0.004	0.819	5.542	6.173	1085	−0.055
2021	1350	3803	0.004	0.824	5.634	6.424	1119	−0.068
2022	1222	3272	0.004	0.803	5.355	5.975	1036	−0.088
2023	1244	3483	0.005	0.809	5.600	6.625	1095	−0.076
2024	1560	5061	0.004	0.819	6.489	7.551	1452	−0.120
All	4733	191,138	0.002	0.841	8.087	9.262	4497	−0.099

Column variables: n-total number of nodes; m-total number of links; d-network density; c-average clustering coefficient; z-average degree; s-average strength; lc-the size of largest component; r-degree pearson correlation coefficient (average assortativity).

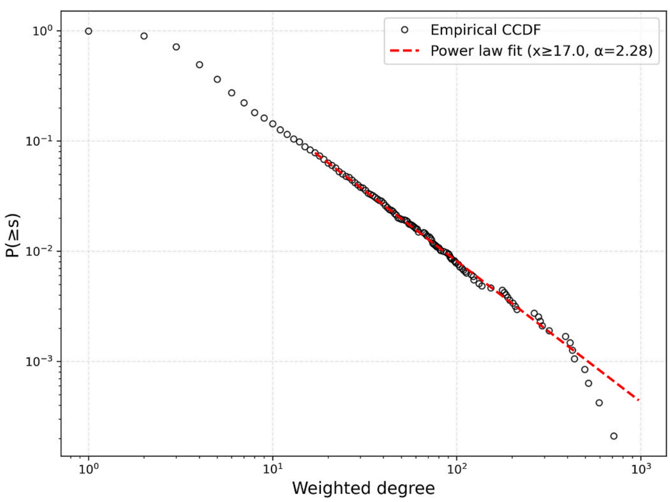

Fig. 3. Complementary cumulative distribution function of weighted degrees (circles), with corresponding power law fit (dashed red line).

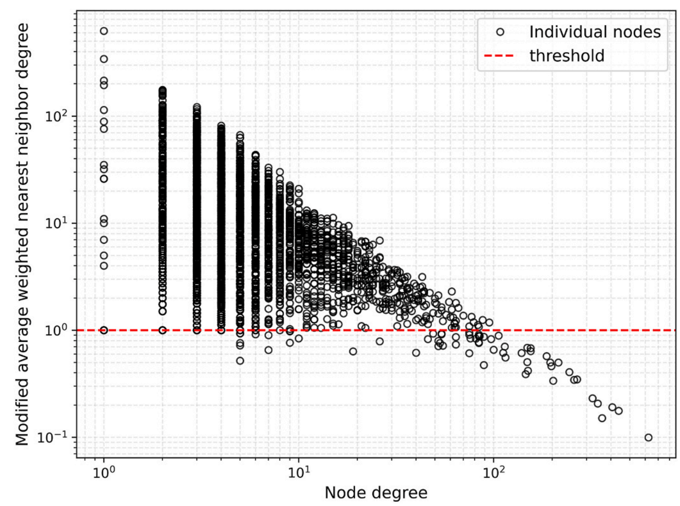

Fig. 5. Average weighted nearest neighbor degree vs. node degree (circles), with a threshold dashline indicating the tendency to associate with lower or higher degree nodes.

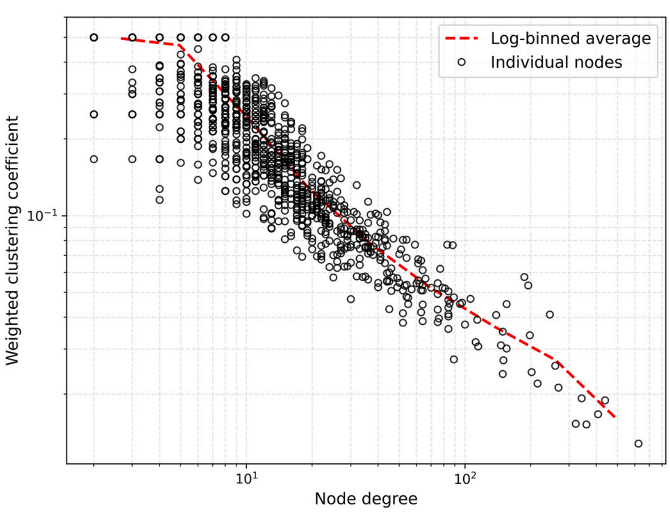

Fig. 4. Node weighted clustering coefficient vs. node degree (circles), with corresponding average for nodes with similar degree (dashed red line).

'learning analytics', 'artificial intelligence', 'massive open online courses', and 'intelligent tutoring systems' suggest that these clusters frequently intersected and jointly drove innovation. For instance, intelligent tutoring systems were increasingly leveraging NLP and AI technologies for automated essay scoring and feedback, conversational Q&A, and the detection of knowledge mastery during learning (Albano et al., 2023; Smerdon, 2024; Vasić et al., 2023). Likewise, learning analytics was widely used on MOOC platforms to track and analyze learners' paths, interaction logs, and post content, enabling the prediction of student performance and personalized recommendations (Hsu & Tutwiler, 2022; C. Thomas et al., 2022).

To examine trends in knowledge clusters, the current study also produced chronological visualizations of the temporal knowledge cluster networks from 2020 to 2024 (see Fig. 7 below). Comparison of these visualizations reveals that topics such as 'natural language processing', 'learning analytics', 'massive open online courses', 'intelligent tutoring systems' and 'self regulated learning' remained consistently prominent areas of focus, underscoring the sustained interests in these topics within the AIED field.

'**Natural language processing**' (NLP) formed the largest knowledge cluster, underscoring its foundational role in creating interactive and responsive educational tools. This cluster's significance lies in its direct contribution to achieving personalized and adaptive learning, a core goal of AIED. The advancements driven by models like BERT and GPT moved beyond simple pattern matching to enable deep language comprehension for tasks like sentiment analysis and text classification, thereby allowing AI systems to understand and respond to student inputs in a more human-like manner (Cochran et al., 2022; Funayama et al., 2023; Ndukwe et al., 2020; Rodrigues, Dwan Pereira et al., 2024).

'**Learning analytics**' (LA) emerged as a central cluster focused on data-informed understanding and optimization of learning processes. Its importance is rooted in the shift towards evidence-based education, where single-mode or multimodal data is used to analyze learning processes. Learning analytics was widely applied in diverse contexts to identify patterns related to self-regulated learning, collaborative learning, and feedback provision (Boulahmel et al., 2024; Chandrasekaran et al., 2022; F. Jin et al., 2024). Artificial intelligence techniques provide the essential computational techniques for modeling, analyzing, and interpreting complex educational dataset (L.Yan et al.,

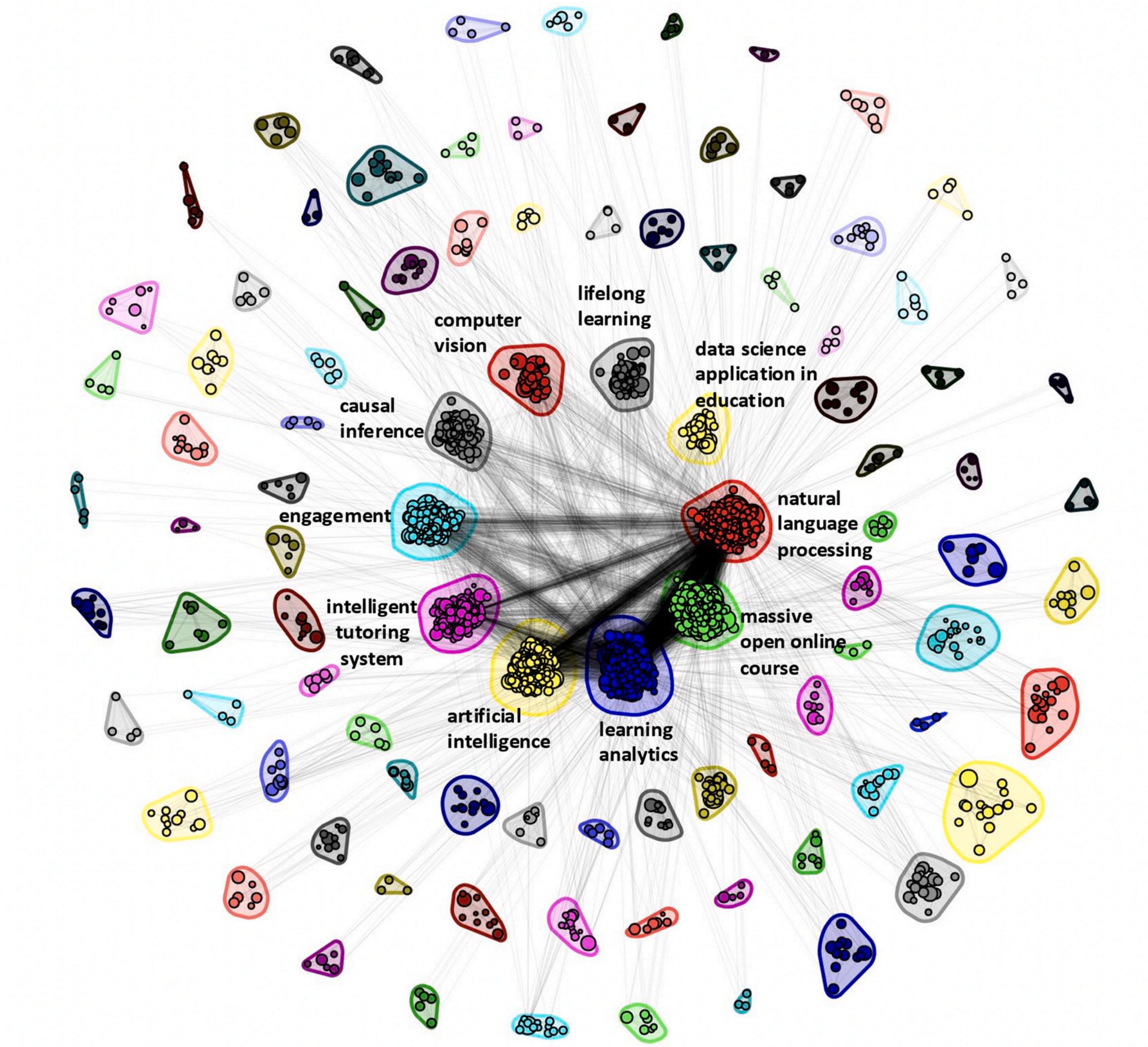

Fig. 6. Knowledge clusters of AIED field from 2020 to 2024, with the top 10 largest knowledge clusters labelled in the graph.

2024; Dang et al., 2024).

'**Massive open online course**' (MOOC) is a significant form of online learning and has been extensively implemented in higher education contexts. It represents a pivotal cluster addressing the challenges of scalability and accessibility in education. MOOC platforms serve as a vital source of large-scale datasets that enable advanced AI research in education. In turn, AI provides the essential methodologies to analyze this data and power these personalized features. Researchers utilize MOOC platforms to collect detailed data on student behaviors, which enables the construction of personalized learner profiles and the provision of tailored learning support (Ahmed et al., 2024; Meaney & Fikes, 2022; Valle Torre et al., 2020). Furthermore, ethical considerations remain a significant concern. Scholars investigated various strategies to safeguard student privacy, including local data storage and the implementation of Differential Privacy techniques to protect sensitive information (Salman & Alexandron, 2024; Valle Torre et al., 2020).

'**Intelligent tutoring system**' (ITS) remained a core and enduring cluster in the field. The cluster's importance is demonstrated by its focus on structuring complex knowledge domains—such as aviation and programming—using ontological approaches as a basis for assessing student performance or making content recommendations (Feitosa et al., 2025; Litovkin et al., 2022; Tchio et al., 2024). Some studies developed cognitive agents based on the ACT-R cognitive architecture integrated with an ontological reference model to simulate how humans perceive, understand, and perform tasks in authentic settings (Hayashi & Shimojo, 2022; Tchio et al., 2024). By integrating intelligent algorithms, these systems can simulate, guide, automate, and recommend instructional activities, enabling more advanced instructional and cognitive support (Chanaa & El Faddouli, 2020; Courtemanche et al., 2023).

'**Self-regulated learning**' (SRL) appeared to be a key knowledge cluster within the field. It refers to the process by which students periodically adjust their learning behaviors to achieve specific learning goals, and its application in online education is particularly widespread. Some researchers integrated SRL with learning analytics LA to examine students' behavioral patterns during this process using multi-source data (Ng et al., 2023; Quick et al., 2023). Other studies explored methods to enhance SRL skills, such as incorporating learner confidence feedback and learner control to facilitate adaptive practice (H. Yan et al., 2024), utilizing technology-supported instructional strategies like videos and prompts, and integrating chatbots (M. Lin & Chang, 2023). Additionally, some researchers investigated the factors that influence SRL, including personality traits (Weng et al., 2024) and reflective abilities (Y. Li et al., 2023).

Based on the analysis of knowledge clusters for the temporal KCNs, it could be noticed that several new knowledge clusters gained a growing interest within the field, including large language model, conversational agent, automatic question generation, human computer interaction,

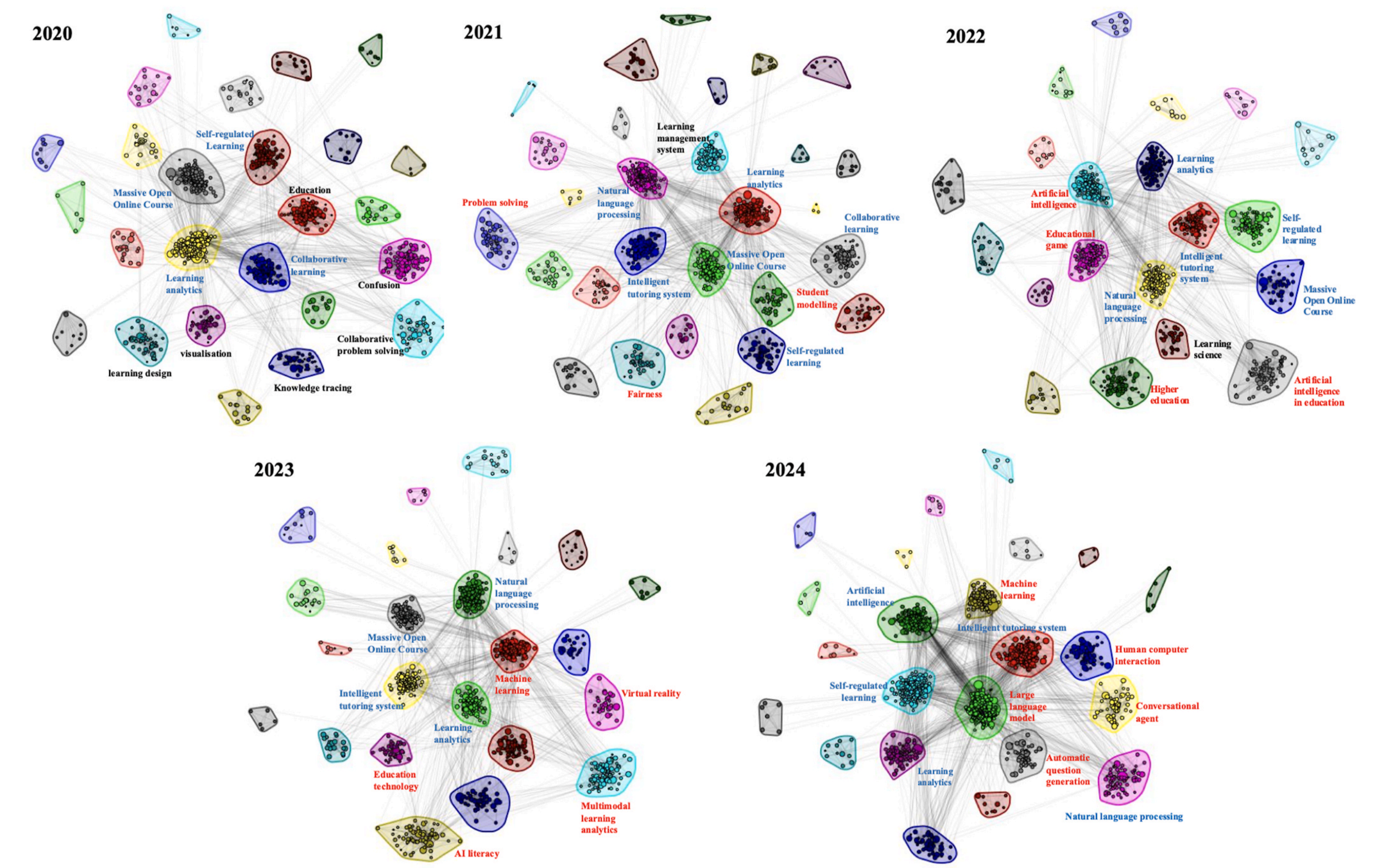

Fig. 7. Temporal knowledge clusters of AIED field from 2020 to 2024.

multimodel learning analytics, virtual reality, and AI literacy.

'**Large language model**' (LLM) represents an emerging knowledge cluster in 2024, highlighting the field's fast adaptation to technical development. Based on the literature within this cluster, LLMs have been mainly used in three aspects: as dialogic partners, as dynamic content generators, and as a new analytical tool. As dialogic partners, LLMs were used to power intelligent tutoring agents that facilitate knowledge development and collaborative problem-solving through conversational interaction (Demetriadis & Dimitriadis, 2023; Shahriar & Matsuda, 2024). As dynamic content generators, LLMs were used to expand learning resources by automating instructional content generation, adjusting content difficulty, and generating practice exercises, thereby providing rich and personalized learning materials (Arif et al., 2024; Jamet et al., 2024; Schmucker et al., 2024; Smith et al., 2024). Furthermore, as a new analytical tool, LLMs were used to identify students' cognitive and emotional states in real-time, offering data-driven insights for educational support—from detecting negative student self-talk to analyzing teacher-student interactions (D. Thomas et al., 2024; Y. Jin & Yu, 2024). A central challenge and focus of ongoing research remains leveraging these capabilities to achieve personalized, scalable, and accurate assessment and feedback (Rodrigues, Pereira, et al., 2024; Sonkar et al., 2024).

'**Conversational agent**' (CA) interacts with learners through text or verbal communication for a given designed learning pru. Many studies have explored various design approaches, such as enhancing learner control (through learning paths and interface appearance), altering agent language and text structures, integrating augmented reality to simulate real-world scenarios, and developing dialogue agents based on learning analytics and fuzzy rules, to examine their effects on learners' cognitive and non-cognitive development (Du & Daniel, 2024; H. Li, Cheng, et al., 2024; Sosnowski et al., 2023; Wambsganss et al., 2025). CA technology evolved from its initial reliance on pattern-matching based on regular expressions to complex systems that leverage machine learning for enhanced user input recognition (Sosnowski et al., 2023). Notably, the rise of GenAI breathed new life into CA. Kakar et al. (2024) proposed a ChatGPT-based CA that demonstrates improved answer accuracy and reduced false positive rates. Additionally, they introduced methods to mitigate hallucinations and harmful content.

'**Automatic question generation**' (AQG) produce formative practice questions tailored to learning texts, aligning with the "learning by doing" philosophy thus effectively enhancing learning outcomes (B. Johnson, Van Campenhout, et al., 2024). By leveraging various NLP techniques, such as the TextRank algorithm, combined with templates, a rich variety of question types—including fill-in-the-blank, multiple-choice, and matching questions— can be generated (Brown et al., 2024; Van Campenhout et al., 2023). With the advancement of AI technologies, researchers have begun exploring the use of GPT to assist in question generation and provide feedback (Diwan et al., 2023; Van Campenhout et al., 2024). Throughout this process, particular attention has been paid to the quality and appropriateness of the generated questions (B. Johnson, Dittel, & Van Campenhout, 2024).

'**Human-Computer Interaction**' (HCI) primarily focuses on how human users effectively communicate with computer systems within educational contexts. This cluster is vital because it ensures that technological advancements are grounded in user needs. Research on gesture recognition, facial movement capture, and interface design emphasizes that for AIED to be effective, the interaction between the human user and the system must be intuitive, engaging, and accessible (Bonyad Khalaj et al., 2024; Nishida et al., 2022, pp. 368–373; Sheel et al., 2024; J. Wang et al., 2023).

'**Multimodal learning analytics**' (MMLA) emerged as a new knowledge cluster independent from learning analytics in 2023, underscoring the importance of analyzing and modeling multi-source, large-scale, and complex educational data. Its importance lies in addressing the limitation of traditional analytics that rely on a single data source. By leveraging sensor technology and AI to analyze complex, multi-source data, MMLA aims to capture a finer-grained, more dynamic picture of learning processes, including aspects like collaboration and emotion that are difficult to measure otherwise (Ouhaichi et al., 2023).

'**Virtual reality**' (VR) technology offers unique advantages for education through its high level of immersion. Its significance lies in its ability to generate authentic, situated experiences while simultaneously acting as a rich, multi-modal data collection platform. AI algorithms process this data—including user movement, gaze, and physiological responses—to make these environments responsive and adaptive (Ng et al., 2022; Seo et al., 2023). Research in this cluster uses VR not only for knowledge development but also as a controlled environment to study and support cognitive states like attention and mental fatigue, thereby bridging experiential learning with cognitive tutoring (Assaf et al., 2023; Y. Chen et al., 2023; Ng et al., 2022; Seo et al., 2023; Zarour et al., 2023).

'**AI literacy**' is critical for equipping students with the skills necessary to navigate future societal transformations. Its emergence reflects the field's recognition that educational outcomes must include the competence to understand, use, and critically evaluate AI. Southworth et al. (2023) introduced the UF AI Literacy Model, including enabling AI,

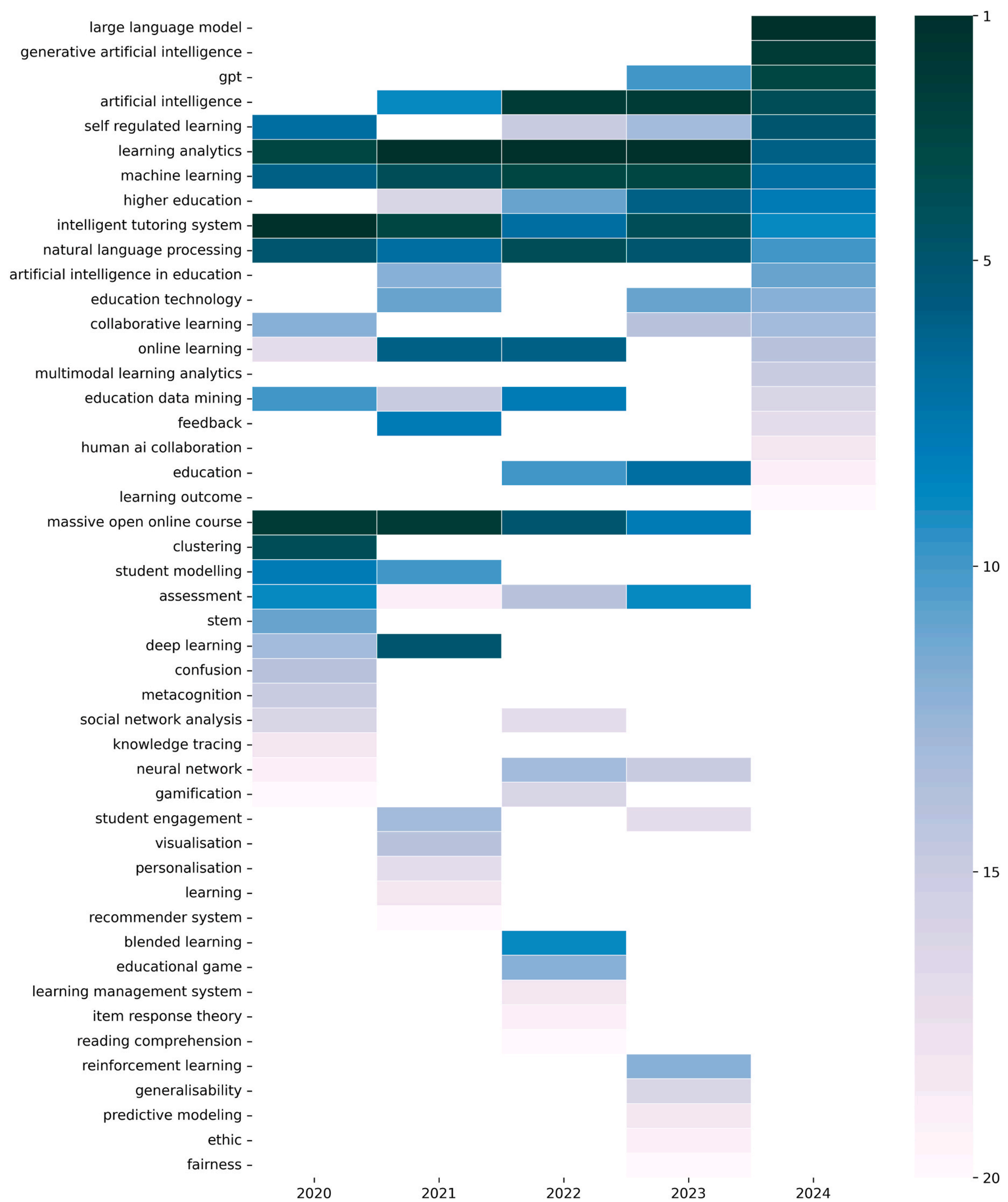

Fig. 8. Top 20 highest weighted betweenness centrality keywords across five time periods.

know & understand AI, use & apply AI, evaluate & create AI, and AI ethics. Due to the limitations of K-12 learners' foundational knowledge and cognitive abilities, researchers have developed varied definitions and curricular designs for AI literacy (J. Su et al., 2023; Yim, 2024). Some researchers have also developed various tools to assess students' AI literacy (Hornberger et al., 2023; Zhang et al., 2025).

4.4. *Emerging frontiers in the AIED field (RQ3)*

Newly emerged keywords with high betweenness centrality merit special attention, as they reveal nascent interdisciplinary topics that bridge distinct fields and foster new research synergies. By tracing the top 20 highest weighted betweenness centrality nodes across the last five years of 2020–2024, this study identified the emerging frontier of the AIED field based on the keywords that first appeared in the top 20 list (see Fig. 8 below). The four emerging frontiers were—**large language model, generative artificial intelligence, human-AI collaboration, and multimodal learning analytics**. These were particularly important for signaling future directions in artificial intelligence in education. The reminder of the section provides a detailed analysis of these emerging topics. The ego network of each emerging themes was extracted, labeling the top 20 alters with the highest degrees to support the interpretation of the emerging themes.

The first emerging frontier was **large language models (LLMs)** (see Fig. 9). It became the keyword with the highest betweenness centrality in 2024 for the first time, reflecting its rising prominence in AIED research. LLMs are built using machine learning—especially deep learning techniques—and serve as a cornerstone for modern NLP, such as sophisticated language understanding and generation. LLMs have been integrated with educational chatbots and are widely applied in areas such as instruction and feedback, greatly improving the quality and adaptability of their responses. For instance, Y. Wang, Guo, et al. (2024) proposed a learning framework with a chatbot-based integrated development environment for programming and testing that uses LLMs and strategy games to generate real-time training data and data-driven improvements.

The integration of LLMs with traditional AIED research domains, such as intelligent tutoring systems and MOOCs, is becoming increasingly prominent. For instance, a ChatGPT-based intelligent tutoring system, PyTutor, employs a phased strategy—including pseudocode, fill-in-the-blank exercises, and tiered code hints—to simulate teacher guidance and adapt to varying levels of task difficulty and student proficiency (A. Yang et al., 2024). This approach has been shown to significantly enhance students' classroom engagement and assignment completion rates (A. Yang et al., 2024). In addition to simulating the role of a teacher, LLMs also have the potential to act as learning partners, enriching the learning experience by offering diverse perspectives on problem-solving (Arnau-Blasco et al., 2024). Providing learners with timely and effective feedback remains a significant challenge in large-scale online courses. To address this issue, automated grading functionalities based on LLMs are increasingly being integrated into online learning platforms to enhance the intelligence and efficiency of assignment evaluation. The multi-agent architecture EvaAI proposed by, as well as the Gipy application for programming assessment developed by Gabbay and Cohen (2024), have both explored this area in depth. The analysis of LLMs applications across educational domains revealed its considerable potential for promoting personalized learning. Unlike traditional personalized learning systems, which require complex design, LLMs substantially lowers the barriers to personalized learning technologies. LLMs leverage powerful pre-trained models and flexible conversational interfaces to assess learning states and dynamically generate contextually relevant dialogues, prompts, thereby fostering dynamic, immersive learning experiences (W. Johnson, 2024; H. Li, Guo, et al., 2024; Naik et al., 2024). LLMs can thoroughly analyze students' background information and historical problem-solving data to achieve more accurate student modeling (Nguyen et al., 2024). Beyond cognition, it can also incorporate emotion recognition to offer tailored encouragement and support motivation (Gaeta et al., 2024).

The second emerging frontier in the field is **Generative Artificial Intelligence** (see Fig. 10) which is a significant branch of artificial intelligence research. From the ego network of GenAI, this study found that the field's current research interests of GenAI are centered around GenAI-driven personalization, self-regulated learning, feedback, assessment, motivation, and ethics. Large language models like GPT-3 exemplify this area, alongside other foundation models for vision and audio (Gupta et al., 2024; Paaβ & Giesselbach, 2023). As GenAI encompasses LLMs, certain alters in the ego networks overlap, such as higher education, assessment, feedback, learning analytics and self-regulated learning. Higher education serves as a prime setting for

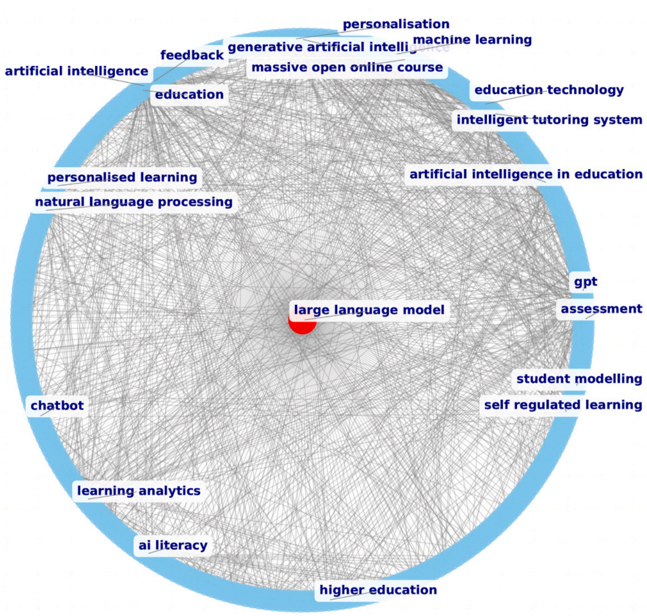

Fig. 9. The ego networks of the first emerging theme *large language model*, with labels for the top 20 alters by degrees.

Fig. 10. The ego network of the second emerging theme *generative artificial intelligence*, with labels for the top 20 alters by degrees.

experimenting with GenAI. Most studies primarily examine policies, current applications, challenges, and future directions, with key challenges including faculty competence, hardware infrastructure, and equity (Chiu, 2024; Y. Jin et al., 2025; H. Wang, Dang, et al., 2024). Given that GenAI is a relatively new technology, researchers are especially interested in the motivation of both teachers and students to engage with it. Studies have found that both groups generally acknowledge the supportive role of GenAI in learning, and that intrinsic motivation (such as interest and a sense of satisfaction) as well as external expectations and self-concept can enhance their willingness to use these tools (Huang & Mizumoto, 2024; Lai et al., 2023; Nikou et al., 2024). However, evidence regarding whether GenAI can increase students' motivation to engage with course content remains inconclusive, underscoring the need for further development of motivation measurement instruments tailored to AI-related contexts (Guan et al., 2025; Lai et al., 2023).

In learning analytics—which involves a cyclical process of learners, data, metrics, and intervention (Clow, 2012)—GenAI enhances functionality by processing unstructured data, generating synthetic learning data, supporting multimodal interactions, and improving the interactivity and interpretability of analyses, thereby facilitating personalized and adaptive interventions (L. Yan, Martinez-Maldonado et al., 2024). In assessment and feedback, existing studies have employed multimodal large models in GenAI (e.g., text, images, speech, video) to enhance interactivity and formative assessment efficiency (Cropley & Marrone, 2025; J. Lin et al., 2024). Moreover, GenAI holds promise for empowering self-regulated learning by supporting students in goal setting and planning based on their behavioral data, monitoring and analyzing their learning behaviors through automated analysis of thought processes, and providing interactive feedback, supplementary information, and guidance for reflection through dialogue (Goslen et al., 2025; Kumar et al., 2024; J. Zhang et al., 2024). Notably, ethical issues—especially academic integrity—are prominent in GenAI research. AI-assisted writing increases risks of plagiarism and undermines originality, highlighting the need for strict policies and education (H. Li, Lee, & Botelho, 2024).

The third emerging topic is **Multimodal learning analytics (MMLA)** (see Fig. 11), which involves collecting and integrating diverse data sources to comprehensively understand learning and its complex processes (Blikstein & Worsley, 2016). MMLA has found applications in multiple domains such as computer programming, science games and online learning, with particular focus on collaborative learning (Fonteles et al., 2024; Ma et al., 2022). Unlike traditional analytics—restricted to log data or test scores—MMLA captures the nuanced group dynamics essential to knowledge co-construction. By integrating various forms of data, MMLA reconstructs dynamic interactions, individual roles, emotional states, conflicts, and rapport within groups (Chejara et al., 2023; Fahid et al., 2023; Z. Wang, Ng, et al., 2024). For example, Y. Ma et al. (2022) employed linguistic, audio, and video modalities to jointly detect impasse states during students' collaborative problem-solving processes. Z. Wang, Ng, et al. (2024) analyzed collaborative patterns among students in maker activities using electroencephalography (EEG), eye-tracking, and system log data. Z. Li, Jensen, et al. (2024) designed the mBox learning platform, which leverages low-cost wearable badges and Internet of Things (IoT) technologies to enable the collection, synchronization, and analysis of multimodal data from collaborative learning groups. Moreover, the abundance of data can increase users' cognitive load and has prompted research into more effective presentation of complex datasets through learning analytics dashboards. L. Yan, Zhao et al. (2024) introduced VizChat, a system capable of visualizing multiple sources of information, such as student locations and student-patient dialogues. By transparently explaining data analysis processes and providing personalized responses, VizChat offers robust support for educational decision-making. In particular, the selection of data types and analytic methods is crucial. Commonly employed data modalities include behavioral data, physiological signals, eye-tracking metrics, facial expressions, audio features, textual data and spatial data representing learners' physical locations (Chejara et al., 2023; Feng et al., 2024; Fonteles et al., 2024; Lämsä et al., 2024; Ma et al., 2022; Schneider & Sung, 2024). In multimodal learning analytics, it is meaningful to compare different modalities as well as to contrast unimodal with multimodal models (Emerson et al., 2023; Mangaroska et al., 2020; Rajarathinam et al., 2024). Empirical evidence indicates that multimodal data substantially improve learning outcome predictions and uncover behavioral patterns undetectable by unimodal approaches (Acosta et al., 2024; Fahid et al., 2023).

The fourth emerging topic in AIED field is **Human-AI collaboration** (see Fig. 12), involving joint efforts between human intelligence and AI algorithms in knowledge work to reach informed results (Puranam, 2021). On the one hand, research highlights the importance of involving

Fig. 11. The ego network of the third emerging theme *multimodal learning analytics*, with labels for the top 20 alters by degrees.

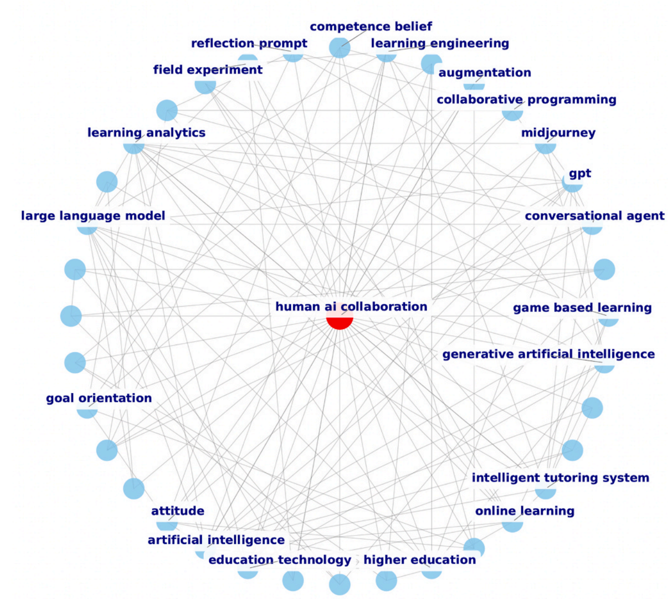

Fig. 12. The ego network of the fourth emerging theme *human AI collaboration*, with labels for the top 20 alters by degrees.

users to improve AI outcomes and correct or supplement AI judgments (Myint et al., 2024; Sun et al., 2024). Aslan et al. (2024) designed "Kid Space", a multimodal and immersive game-based learning system aimed at enhancing children's mathematical performance while promoting physical activity and social interaction. Since deep learning components have not yet achieved human-level understanding in dialogue systems, human experts monitor all learning content and student activities in the space and promptly intervene to correct any errors made by the system (Mosqueira-Rey et al., 2023). On the other hand, AI can simplify human actions and enhance work efficiency. According to Brusilovsky (2024), AI supports teacher and learner decisions through mechanisms such as ranking relevant content, providing annotations and explanations, and offering navigation guidance to optimize learning paths. Human-AI dialogue is an important form of achieving human-AI collaboration. Dialogue, primarily based on language models, enables students to engage in personalized interactions with conversational agents. By reflecting on and adjusting their study based on the machine's responses in scenarios such as collaborative programming, students can enhance their learning outcomes and confidence (Kumar et al., 2024; Sankaranarayanan et al., 2021). Human-AI collaborative learning presents new opportunities and challenges for learning analytics. Technologies such as GenAI may mimic certain learning processes and produce learning outcomes, making it challenging to define "the very essence of what it means to be a learner" (L. Yan, Martinez-Maldonado et al., 2024, p.103). Therefore, learning analytics should not only capture human data but also gather computational data to explore the collaborative processes effectively (L. Yan, Martinez-Maldonado et al., 2024). Beyond these technical dimensions, researchers also investigate human attitudes toward AI. AI's rapid advancement naturally generates anxiety, manifesting in two distinct responses: some avoid AI use altogether, while others are motivated to develop better collaboration skills with these technologies (Kaya et al., 2024). L. Xu et al. (2023) explored human-centered design and careful presentation of algorithm-based recommendations can reduce resistance from users—particularly domain experts—toward machine-generated decisions. Guggemos (2024) suggests our focus should shift from fearing AI replacement to leveraging AI to enhance everyday work.

5. Discussion

5.1. The three-level analysis of the AIED field

This study systematically analyzed the current foci and emerging topics in the AIED field. From a macro perspective, as showed by the results related to RQ1, the knowledge structure of AIED research exhibited a hierarchical structure with several core keywords as hubs linking a wide variety of research topics. At the meso-level (RQ2), sustained themes in AIED, including natural language processing and intelligent tutoring systems have been identified. At the micro-level (RQ3), emerging frontiers of the field are identified including large language models, generative AI, multimodal learning analytics, and human-AI collaboration.

The macro-level analysis results revealed that the AIED field possesses a hierarchical knowledge structure. This is evidenced by a network topology with a heavy-tailed degree distribution and a high clustering coefficient identified in RQ1. This structure signifies that the field is neither fragmented nor randomly organized; instead, it is efficiently integrated around a small set of core, highly connected concepts that act as knowledge hubs (Ravasz & Barabási, 2003). These hubs—keywords like those identified in the central clusters (e.g. ITS, NLP)—anchor the entire research landscape, facilitating the flow of ideas and ensuring thematic coherence (Kirkley, 2024). The presence of this architecture indicates a maturing field where foundational pillars effectively connect diverse sub-communities, providing a stable scaffold upon which new, emerging frontiers can converge and develop.

The meso-level analysis results revealed the coherent knowledge clusters of the AIED field. The identification of prominent clusters such as 'natural language processing' (NLP), 'intelligent tutoring systems' (ITS), 'massive open online courses' (MOOCs) demonstrates a thematic stability, directly aligning with the persistent themes identified by Feng and Law (2021) for the preceding decade. This study also identified new research themes centered to the field in the GenAI era, that were not observed in the previous decade, such as self-regulated learning. The focus on concepts like self-regulated learning underscores a continued commitment to fostering learner autonomy and human agency (Edwards et al., 2025; Giannakos et al., 2022; Järvelä et al., 2021).

The micro-level analysis revealed the new interests driven by the emerging technologies in the GenAI contexts, including Large Language Models, Generative AI, Multimodal Learning Analytics, and Human-AI Collaboration. While 'Natural Language Processing' has long been a stable cluster within the field, the emergence of LLMs and GenAI represents the increasing applications of these techniques on handling text data in education applications (Demetriadis & Dimitriadis, 2023; Kumar et al., 2024; Naik et al., 2024). These technologies have become critical for generating personalized and timely feedback, support, and educational content (Arif et al., 2024; J. Lin et al., 2024; Sonkar et al., 2024). Simultaneously, multimodal learning analytics (MMLA) is providing powerful tools to advance the study of learning processes (Chejara et al., 2023; Feng et al., 2024; Schneider & Sung, 2024). Specifically, our analysis results (Fig. 11) revealed that multimodal learning analytics (MMLA) was structurally connected to established, core knowledge clusters identified in our meso-level analysis, including collaborative learning, collaborative problem solving, intelligent tutoring systems, and self-regulated learning. This demonstrates the importance of MMLA in studying social engagement, metacognitive development, and adaptive scaffolding in the current GenAI context. Lastly, the rise of Human-AI Collaboration marks a critical evolution, emphasizing a swift focus from AI-driven automation to AI as a collaborative partner in the learning process (Järvelä, Nguyen, & Hadwin, 2023; Puranam, 2021).

Together, these three-level analysis results provide a new map of the AIED landscape at the onset of GenAI era. The macro-level reveals a hierarchical structure indicating a strong core focus alongside diverse topic coverage, while the meso-level identifies sustained clusters—such as ITS and NLP—that reveal the fundamental focus of the field towards creating personalized learning pathways through advanced analytics. The micro-level uncovers emerging frontiers like Human-AI Collaboration and MMLA, which indicate a paradigm shift towards human-centered development. *This three-level analysis demonstrates that the AIED field is built upon a foundation of robust, enduring themes dedicated to core educational challenges: **personalization through advanced analytical techniques and the development of human learning capabilities**.*

5.2. Human-AI collaboration

Of the four identified emerging frontiers, human–AI collaboration stands out as a distinct, theoretically-grounded theme, contrasting with the more method and technology-oriented frontiers of LLMs, GenAI, and multimodal learning analytics. Our results (Fig. 12) revealed its connections to "learning analytics," "conversational agents," "intelligent tutoring systems," "generative artificial intelligence," and "large language models." This demonstrates its role as a critical bridge between advanced AI technologies and their educational application. Human-AI collaboration emphasizes mutual learning, cooperation, and reinforcement between humans and machines (Järvelä, Nguyen, & Hadwin, 2023). A powerful theoretical lens for understanding this frontier is the vision of hybrid intelligence, which promotes the co-evolution and adaptation of human and AI to amplify collective problem-solving capabilities (Cukurova, 2024; Molenaar, 2022). Complementing this, Järvelä, Zhao, et al. (2023) introduced the Human–AI Shared Regulation in Learning (HASRL) framework, which highlights the dynamic interplay where learners and AI systems co-regulate learning processes and products. This theoretical perspective places particular emphasis on how cognitive and regulatory resources are circulated and shared, positioning AI as an integral component of the cognitive system that can externalize, internalize, or extend human cognition (Cukurova, 2019, 2024; Gašević et al., 2023).

The findings of the current study confirm the significant research attention to human-AI collaboration in the AIED field, yet there remains a long way to go. Although theories such as the HASRL framework provide a foundational design principle for human-AI collaboration, there is still a lack of effective methods and strategies for developing the adaptive and personalized AI interventions required for clearly defined shared regulation (Mustafa et al., 2024). In the future, the theoretical exploration of human-AI collaboration requires new AI-powered learning analytical methods, a deeper integration of multidisciplinary theories and multi-tiered approaches, while its application may focus on the diverse roles of AI and the capacity to address complex tasks (Gašević et al., 2023; Jiang et al., 2024). It is also important for human collaborators to enhance their AI literacy and understand how to more effectively collaborate with AI systems to realize the vision of hybrid intelligence.

5.3. *Critical tensions and future suggestions*

The present study revealed the primary foci of contemporary AIED research, which centers on developing AI-assisted systems and using AI to support educational analysis. This is evidenced by the results that the majority of the identified clusters are technically oriented, such as 'natural language processing' (Cluster 1), 'learning analytics' (Cluster 2), artificial intelligence' (Cluster 4), and 'intelligent tutoring system' (Cluster 6). A few clusters focus on learning contexts and applications—such as 'massive open online course' (Cluster 3) and 'engagement' (Cluster 5). While this technological drive is essential, the analysis results led us to stress a critical imperative for the field: it is essential to proactively bridge these advanced technical capabilities with core educational values and purposes to ensure that technological development is meaningfully aligned with human learning needs.

The technical approaches evident in clusters like 'multimodal learning analytics' (Cluster 2) and 'engagement' (Cluster 5, featuring 'eye tracking' and 'classification')—which seek to manage complex data streams from text to vision—inherently generates ethical challenges. This direct link is also seen by the co-occurrence of 'ethic' and 'privacy' with 'personalization' in the 'massive open online course' cluster (Cluster 3). This structural relationship indicates that the drive for personalization and data-intensive analysis creates persistent tensions with data protection imperative. Critical questions concerning the effective use of such information remain unresolved, such as how to responsibly interpret multimodal data, whether data-driven feedback should be primarily preventive or corrective, who should be tasked with providing feedback, and the extent to which students ought to be informed about behavioral data collected about them (Sharma & Giannakos, 2020). To address these challenges, the establishment of robust data governance frameworks that regulate policies and procedures for data quality, security, and privacy is imperative (CLNR, 2025). The development of efficient tools and algorithms for data processing is likewise necessary to enhance the collection, annotation, and interpretation of educational data (Cukurova et al., 2020). Holmes and Tuomi (2022) emphasize, the ethics of AI in education must also encompass broader educational ethics considerations, including pedagogy, assessment practices, knowledge, and student and teacher agency.

Moreover, ongoing data literacy training for educators is crucial, ensuring that the wealth of educational data genuinely enhances teaching and learning rather than introducing additional complexity. In classroom practice, the integration of GAI tools into curricula and the use of multimodal data significantly raise the demands placed on teachers' competencies. Our structural map revealed a critical finding: while clusters like 'intelligent tutoring system' (Cluster 6) and 'artificial intelligence' (Cluster 4) focus on applications, there is no prominent cluster dedicated to teacher professional development. This structural gap indicates a major implementation risk. Empowering teachers is essential for managing the complexities of GAI and forming constructive partnerships with AI (Kim, 2024; Marzano, 2025), a necessity confirmed by other reviews (Tan et al., 2025).

The entire research architecture, from stable technical clusters to emerging frontiers, exists within a policy context. We argue that to guide this ecosystem toward human-centered ends, policy should consider actively promoting ethical frameworks and embedding AI literacy into curricula (Allison et al., 2025; Ifenthaler et al., 2024). Large-scale and longitudinal research efforts, incorporating interdisciplinary collaboration, are needed to generate more robust evidence in this area (K. Zhang & Aslan, 2021). Strategies and mechanisms should also be established to facilitate the integration of research findings into teaching and learning practices (Isotani et al., 2023; Lai et al., 2023).

6. Conclusion

This study provides an updated and systematic analysis of the AIED landscape and identifies the current research foci and emerging topics. The current study showed that research in AIED exhibits both stability and considerable dynamism, driven by technological advancements and changing educational demands. Core areas such as intelligent tutoring systems, learning analytics, natural language processing, and MOOCs continue to play key roles in improving learning outcomes and enhancing learner experience. Four key emerging frontiers are identified: (1) LLMs, (2) GenAI, (3) multimodal learning analytics, and (4) human-AI collaboration.

Several limitations of this study should be acknowledged. First, while our keyword co-occurrence network analysis provides a powerful macro-level map of the field's structure and emerging frontiers, this bird's-eye view inherently sacrifices the deep, contextual nuance that comes from fine-grained, qualitative analysis. Future studies should triangulate these structural findings with qualitative methods, such as ethnographic studies in authentic classrooms or experimental studies on specific AI interventions, to provide richer, multi-faceted insights into the human experiences and educational outcomes within clusters like human-AI collaboration. Second, the analysis relied on keywords and metadata without incorporating other bibliometric attributes, such as author networks and citation patterns. Including these in the future would offer a deeper understanding of scholarly collaboration and knowledge dissemination. Ultimately, the primary contribution of this study is to provide the essential, objective baseline to guide and prioritize such subsequent in-depth investigations.

Future studies are recommended to conduct in-depth reviews and empirical investigations into the emerging frontiers, particularly human-AI collaboration, where the literature is still rapidly evolving. Such work is crucial to move beyond literature mapping and understand the pedagogical models and theoretical frameworks that will inform the future development of human-AI collaboration in the field. Furthermore, AI for education research should consciously resist becoming a purely technocentric endeavor and must be reoriented around human-centered principles— ensuring that technological development is guided by educational goals, ethical considerations, and a commitment to enhancing human agency and equity. Ultimately, this critical reorientation is necessary to ensure that the powerful technologies identified in this review fulfill their promise to support, rather than subvert, the fundamental human processes of teaching and learning.

CRediT authorship contribution statement

Shihui Feng: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Huilin Zhang:** Writing – original draft, Investigation, Data curation. **Dragan Gašević:** Writing – review & editing, Conceptualization, Funding acquisition.

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.

Acknowledgements

This work has been in part suppoted by the Australian Government through the Australian Research Council (DP240100069 and DP220101209) and the Jacobs Foundation (CELLA2 CERES) (Dragan Gasevic), and Hong Kong Research Grant Council under Early Career Scheme (#27605223) (Shihui Feng).

Appendix

Table 1
Top ten highest in-group degree keywords for each knowledge cluster.

Clusters	Top ten highest in-group degree keywords	Clusters	Top ten highest in-group degree keywords
1. 'Natural language processing'	'machine learning', 'large language model', 'deep learning', 'gpt', 'assessment', 'knowledge tracing', 'education', 'bert', 'neural network', 'item response theory'	6. "Intelligent tutoring system"	'ontology', 'student model', 'web ontology language', 'pyactr', 'cognitive agent', 'task ontology', 'domain ontology', 'teacher dashboard', 'act r', 'situation awareness'
2. 'Learning analytics'	'self-regulated learning', 'collaborative learning', 'multimodal learning analytics', 'student modelling', 'education data mining', 'collaborative problem solving', 'feedback', 'clustering', 'motivation', 'computer science education'	7. 'Causal inference'	'programming', 'user experience', 'hint', 'self explanation', 'scheduling', 'python', 'productive 'persistence', 'tutoring system', 'data driven method', 'worked example'
3. 'Massive open online course'	'online learning', 'higher education', 'ai literacy', 'learning management system', 'ethic', 'online education', 'privacy', 'personalization', 'electroencephalograph', 'dashboard'	8. 'Lifelong learning'	'intelligent tutoring', 'adult learning', 'curriculum analytics', 'research method at scale', 'introductory programming course', 'facial emotion recognition', 'principal component analysis', 'social interaction', 'discussion board', 'problem decomposition'
4. "Artificial intelligence"	'generative artificial intelligence', 'artificial intelligence in education', 'student engagement', 'technology acceptance model', 'systematic review', 'computer assisted language learning', 'decision making', 'social medium', 'english language teaching', 'technology in education'	9. 'Computer vision'	'authoring tool', 'classroom analytics', 'augmented reality', 'mixed reality', 'adaptive learning technology', 'conversation analysis', 'design analytics', 'spatial analytics', 'stop detection', 'hyperparameters'
5. "Engagement"	'eye tracking', 'classification', 'topic modelling', 'discussion forum', 'online discussion', 'question generation', 'critical thinking', 'early warning system', 'dialogue system', 'attention'	10. 'Data science application in education',	'evaluation methodology', 'game', 'cooperative/collaborative learning', 'bias mitigation', 'human computer interface', 'post secondary education', 'distributed learning environment', 'improving classroom teaching', 'supervised machine learning', 'application in subject area'

References

Acosta, H., Lee, S., Mott, B., Bae, H., Glazewski, K., Hmelo-Silver, C., & James, L. (2024). Multimodal learning analytics for predicting student collaboration satisfaction in collaborative game-based learning. In *Proceedings of the 17th international conference on educational data mining* (pp. 224–235). https://doi.org/10.5281/ZENODO.12729802

Ahmed, T., Bumbacher, E., Blikstein, P., & Riedel-Kruse, I. H. (2024). Large-scale and versatile deployment of biology cloud labs in schools through teacher driven curricula design. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 524–529). https://doi.org/10.1145/3657604.3664713

Ahmed, N., Saha, A. K., Al Noman, M. A., Jim, J. R., Mridha, M. F., & Kabir, M. M. (2024). Deep learning-based natural language processing in human–agent interaction: Applications, advancements and challenges. *Natural Language Processing Journal, 9*, Article 100112. https://doi.org/10.1016/j.nlp.2024.100112

Albano, V., Firmani, D., Laura, L., Mathew, J. G., Paoletti, A. L., & Torrente, I. (2023). NLP-based management of large multiple-choice test item repositories. *Journal of Learning Analytics, 10*(3), 28–44. https://doi.org/10.18608/jla.2023.7897

Alemdag, E. (2025). The effect of chatbots on learning: A meta-analysis of empirical research. *Journal of Research on Technology in Education, 57*(2), 459–481. https://doi.org/10.1080/15391523.2023.2255698

Ali, O., Murray, P. A., Momin, M., Dwivedi, Y. K., & Malik, T. (2024). The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technological Forecasting and Social Change, 199*, Article 123076. https://doi.org/10.1016/j.techfore.2023.123076

Allison, J., Hwang, G.-J., Mayer, R. E., Pellas, N., Karnalim, O., De Freitas, S., Ng, O.-L., Huang, Y.-M., Hooshyar, D., Seidman, R. H., Al-Emran, M., Mikropoulos, T. A., Schroeder, N. L., Roscoe, R. D., & Sanusi, I. (2025). From generative AI to extended reality: Multidisciplinary perspectives on the challenges, opportunities, and future of educational computing. *Journal of Educational Computing Research, 63*(6), 1327–1363. https://doi.org/10.1177/07356331251359964

An, Q., Yang, J., Xu, X., Zhang, Y., & Zhang, H. (2024). Decoding AI ethics from users' lens in education: A systematic review. *Heliyon, 10*(20), Article e39357. https://doi.org/10.1016/j.heliyon.2024.e39357

Arif, T., Asthana, S., & Collins-Thompson, K. (2024). Generation and assessment of multiple-choice questions from video transcripts using large language models. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 530–534). https://doi.org/10.1145/3657604.3664714

Arnau-Blasco, J., Arevalillo-Herráez, M., Solera-Monforte, S., & Wu, Y. (2024). Using large language models to support teaching and learning of word problem solving in tutoring systems. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 3–13). Springer Nature. https://doi.org/10.1007/978-3-031-63028-6_1.

Aryadoust, V., Zakaria, A., & Jia, Y. (2024). Investigating the affordances of OpenAI's large language model in developing listening assessments. *Computers and Education: Artificial Intelligence, 6*, Article 100204. https://doi.org/10.1016/j.caeai.2024.100204

Aslan, S., Durham, L. M., Alyuz, N., Okur, E., Sharma, S., Savur, C., & Nachman, L. (2024). Immersive multi-modal pedagogical conversational artificial intelligence for early childhood education: An exploratory case study in the wild. *Computers and Education: Artificial Intelligence, 6*, Article 100220. https://doi.org/10.1016/j.caeai.2024.100220

Assaf, A. H., Ben Abdessalem, H., & Frasson, C. (2023). Detecting mental fatigue in intelligent tutoring systems. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 66–74). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_6.

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

Bonyad Khalaj, A., Ben Abdessalem, H., & Frasson, C. (2024). Assessing cognitive workload of aircraft pilots through face temperature. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14799, pp. 27–37). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63031-6_3.

Boulahmel, A., Djelil, F., Gilliot, J.-M., Leray, P., & Smits, G. (2024). Mining discriminative sequential patterns of self-regulated learners. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14799, pp. 137–149). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63031-6_12.

Bozkurt, A., Karadeniz, A., Baneres, D., Guerrero-Roldán, A. E., & Rodríguez, M. E. (2021). Artificial intelligence and reflections from educational landscape: A review of AI studies in half a century. *Sustainability, 13*(2), 800. https://doi.org/10.3390/su13020800

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., … Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901.

Brown, N., Van Campenhout, R., Clark, M., & Johnson, B. G. (2024). Are students reading? How formative practice impacts student reading behaviors in etextbooks. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 383–387). https://doi.org/10.1145/3657604.3664668

Brusilovsky, P. (2024). Ai in education, learner control, and human-AI collaboration. *International Journal of Artificial Intelligence in Education, 34*(1), 122–135. https://doi.org/10.1007/s40593-023-00356-z

Chanaa, A., & El Faddouli, N.-E. (2020). BERT and prerequisite based ontology for predicting learner's confusion in moocs discussion forums. In I. I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial intelligence in education* (Vol 12164, pp. 54–58). Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_10.

Chandrasekaran, D., Chang, M., & Graf, S. (2022). A learning analytics approach to build learner profiles within the educational game omega+. In S. Crossley, & E. Popescu (Eds.), *Intelligent tutoring systems* (Vol 13284, pp. 139–147). Springer International Publishing. https://doi.org/10.1007/978-3-031-09680-8_13.

Chejara, P., Prieto, L. P., Rodriguez-Triana, M. J., Kasepalu, R., Ruiz-Calleja, A., & Shankar, S. K. (2023). How to build more generalizable models for collaboration quality? Lessons learned from exploring multi-context audio-log datasets using multimodal learning analytics. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 111–121). https://doi.org/10.1145/3576050.3576144

Chen, Y., Kay, J., & Yoo, S. (2023). Feedback and open learner models in popular commercial VR games: A systematic review. In N. Wang, G. Rebolledo-Mendez, N. Matsuda, O. C. Santos, & V. Dimitrova (Eds.), *Artificial intelligence in education* (Vol 13916, pp. 541–552). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-36272-9_44.

Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of Artificial Intelligence in education. *Computers and Education: Artificial Intelligence, 1*, Article 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence, 6*, Article 100197. https://doi.org/10.1016/j.caeai.2023.100197

Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, Article 100118. https://doi.org/10.1016/j.caeai.2022.100118

Clauset, A., Newman, M. E. J., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E, 70*(6), Article 066111. https://doi.org/10.1103/PhysRevE.70.066111

CLNR. (2025). Why is data important in education? California learning resource network. https://www.clrn.org/why-is-data-important-in-education/.

Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 134–138). https://doi.org/10.1145/2330601.2330636

Cochran, K., Cohn, C., Hutchins, N., Biswas, G., & Hastings, P. (2022). Improving automated evaluation of formative assessments with text data augmentation. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Artificial intelligence in education* (Vol. 13355, pp. 390–401). Springer International Publishing. https://doi.org/10.1007/978-3-031-11644-5_32.

Courtemanche, M.-A., Tato, A., & Nkambou, R. (2023). Automatic execution of the ontological piloting procedures. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 29–41). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_3.

Cropley, D. H., & Marrone, R. L. (2025). Automated scoring of figural creativity using a convolutional neural network. *Psychology of Aesthetics, Creativity, and the Arts, 19*(1), 77–86. https://doi.org/10.1037/aca0000510

Cukurova, M. (2019). Learning analytics as AI extenders in education: Multimodal machine learning versus multimodal learning analytics. *Artificial intelligence and adaptive education*.

Cukurova, M. (2024). The interplay of learning, analytics, and artificial intelligence in education: A vision for hybrid intelligence. *arXiv:2403.16081*. https://doi.org/10.48550/arXiv.2403.16081. arXiv.

Cukurova, M., Giannakos, M., & Martinez-Maldonado, R. (2020). The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology, 51*(5), 1441–1449. https://doi.org/10.1111/bjet.13015

Dang, B., Nguyen, A., & Järvelä, S. (2024). Deliberative interactions for socially shared regulation in collaborative learning: An AI-Driven learning analytics study. *Journal of Learning Analytics, 11*(3), 192–209. https://doi.org/10.18608/jla.2024.8393

Delen, I., Sen, N., Ozudogru, F., & Biasutti, M. (2024). Understanding the growth of artificial intelligence in educational research through bibliometric analysis. *Sustainability, 16*(16), 6724. https://doi.org/10.3390/su16166724

Demetriadis, S., & Dimitriadis, Y. (2023). Conversational agents and language models that learn from human dialogues to support design thinking. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 691–700). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_60.

Diwan, C., Srinivasa, S., Suri, G., Agarwal, S., & Ram, P. (2023). AI-based learning content generation and learning pathway augmentation to increase learner engagement. *Computers and Education: Artificial Intelligence, 4*, Article 100110. https://doi.org/10.1016/j.caeai.2022.100110

Du, J., & Daniel, B. K. (2024). Transforming language education: A systematic review of AI-powered chatbots for English as a foreign language speaking practice. *Computers and Education: Artificial Intelligence, 6*, Article 100230. https://doi.org/10.1016/j.caeai.2024.100230

Edwards, J., Nguyen, A., Lämsä, J., Sobocinski, M., Whitehead, R., Dang, B., Roberts, A., & Järvelä, S. (2025). Human- AI collaboration: Designing artificial agents to facilitate socially shared regulation among learners. *British Journal of Educational Technology, 56*(2), 712–733. https://doi.org/10.1111/bjet.13534

Emerson, A., Min, W., Rowe, J., Azevedo, R., & Lester, J. (2023). Multimodal predictive student modeling with multi-task transfer learning. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 333–344). https://doi.org/10.1145/3576050.3576101

Fahid, F. M., Lee, S., Mott, B., Vandenberg, J., Acosta, H., Brush, T., Glazewski, K., Hmelo-Silver, C., & Lester, J. (2023). Effects of modalities in detecting behavioral engagement in collaborative game-based learning. In *LAK23: 13th international* *learning analytics and knowledge conference* (pp. 208–218). https://doi.org/10.1145/3576050.3576079

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology, 56*(2), 489–530. https://doi.org/10.1111/bjet.13544

Feitosa, R. G. F., Campos, G. A. L. D., Santos, I. D. S., Gonçalves, C. H. R., Serra, A. D. B., Oliveira, A. R. D., Feitosa, P. L. P., Santos, Y. D., Bispo, E. L., & Esmeraldo, G.Á. R. M. (2025). Competency and skill-based educational recommendation system. *International Journal of Artificial Intelligence in Education, 35*(1), 135–154. https://doi.org/10.1007/s40593-024-00423-z

Feng, S., & Law, N. (2021). Mapping artificial intelligence in education research: A network-based keyword analysis. *International Journal of Artificial Intelligence in Education, 31*(2), 277–303. https://doi.org/10.1007/s40593-021-00244-4

Feng, S., & Tan, C. Y. (2024). Toward conceptual clarity for digital cultural and social capital in student learning: Insights from a systematic literature review. *Humanities and Social Sciences Communications, 11*(1), 1–15.

Feng, S., Yan, L., Zhao, L., Maldonado, R. M., & Gašević, D. (2024). Heterogenous network analytics of small group teamwork: Using multimodal data to uncover individual behavioral engagement strategies. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 587–597). https://doi.org/10.1145/3636555.3636918

Fonteles, J., Davalos, E., Ashwin, T. S., Zhang, Y., Zhou, M., Ayalon, E., Lane, A., Steinberg, S., Anton, G., Danish, J., Enyedy, N., & Biswas, G. (2024). A first step in using machine learning methods to enhance interaction analysis for embodied learning environments. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol. 14830, pp. 3–16). Springer Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-64299-9_1.

Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*(3–5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Funayama, H., Asazuma, Y., Matsubayashi, Y., Mizumoto, T., & Inui, K. (2023). Reducing the cost: Cross-prompt pre-finetuning for short answer scoring. In N. Wang, G. Rebolledo-Mendez, N. Matsuda, O. C. Santos, & V. Dimitrova (Eds.), *Artificial intelligence in education* (Vol 13916, pp. 78–89). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-36272-9_7.

Gabbay, H., & Cohen, A. (2024). Combining LLM-generated and test-based feedback in a MOOC for programming. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 177–187). https://doi.org/10.1145/3657604.3662040

Gaeta, A., Orciuoli, F., Pascuzzo, A., & Peduto, A. (2024). Evaluating the ability of large language models to generate motivational feedback. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 188–201). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_15.

Garzón, J., Patiño, E., & Marulanda, C. (2025). Systematic review of artificial intelligence in education: Trends, benefits, and challenges. *Multimodal Technologies and Interaction, 9*(8), 84. https://doi.org/10.3390/mti9080084

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

Gašević, D., Siemens, G., & Sadiq, S. (2023). Empowering learners for the age of artificial intelligence. *Computers and Education: Artificial Intelligence, 4*, Article 100130. https://doi.org/10.1016/j.caeai.2023.100130

Giannakos, M., Spikol, D., Di Mitri, D., Sharma, K., Ochoa, X., & Hammad, R. (2022). Introduction to multimodal learning analytics. In M. Giannakos, D. Spikol, D. Di Mitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook* (pp. 3–28). Springer International Publishing. https://doi.org/10.1007/978-3-031-08076-0_1.

Goslen, A., Kim, Y. J., Rowe, J., & Lester, J. (2025). LLM-based student plan generation for adaptive scaffolding in game-based learning environments. *International Journal of Artificial Intelligence in Education, 35*(2), 533–558. https://doi.org/10.1007/s40593-024-00421-1

Guan, L., Zhang, E. Y., & Gu, M. M. (2025). Examining generative AI–mediated informal digital learning of English practices with social cognitive theory: A mixed-methods study. *ReCALL, 37*(3), 315–331. https://doi.org/10.1017/S0958344024000259

Guggemos, J. (2024). To fear or not to fear – Human resource development professionals' positioning towards artificial intelligence with a focus on augmentation. *Computers and Education: Artificial Intelligence, 7*, Article 100260. https://doi.org/10.1016/j.caeai.2024.100260

Gupta, P., Ding, B., Guan, C., & Ding, D. (2024). Generative AI: A systematic review using topic modelling techniques. *Data and Information Management, 8*(2), Article 100066. https://doi.org/10.1016/j.dim.2024.100066

Hayashi, Y., & Shimojo, S. (2022). Modeling perspective taking and knowledge use in collaborative explanation: Investigation by laboratory experiment and computer simulation using ACT-r. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Artificial intelligence in education* (Vol. 13355, pp. 647–652). Springer International Publishing. https://doi.org/10.1007/978-3-031-11644-5_62.

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education, 57*(4), 542–570. https://doi.org/10.1111/ejed.12533

Hornberger, M., Bewersdorff, A., & Nerdel, C. (2023). What do university students know about Artificial Intelligence? Development and validation of an AI literacy test. *Computers and Education: Artificial Intelligence, 5*, Article 100165. https://doi.org/10.1016/j.caeai.2023.100165

Hsu, S.-Y., & Tutwiler, M. S. (2022). How much and for whom?: A multi-wave study of the impact of self-regulated learning scaffolds on MOOC student academic performance. In *Proceedings of the ninth ACM conference on learning @ scale* (pp. 350–354). https://doi.org/10.1145/3491140.3528312

Huang, J., & Mizumoto, A. (2024). Examining the relationship between the L2 motivational self system and technology acceptance model post ChatGPT introduction and utilization. *Computers and Education: Artificial Intelligence, 7*, Article 100302. https://doi.org/10.1016/j.caeai.2024.100302

Ifenthaler, D., Majumdar, R., Gorissen, P., Judge, M., Mishra, S., Raffaghelli, J., & Shimada, A. (2024). Artificial intelligence in education: Implications for policymakers, researchers, and practitioners. *Technology, Knowledge and Learning, 29*(4), 1693–1710. https://doi.org/10.1007/s10758-024-09747-0

Isotani, S., Bittencourt, I. I., & Walker, E. (2023). Artificial intelligence and educational policy: Bridging research and practice. In N. Wang, G. Rebolledo-Mendez, V. Dimitrova, N. Matsuda, & O. C. Santos (Eds.), *Artificial intelligence in education. Posters and late breaking results, workshops and tutorials, industry and innovation tracks, practitioners, doctoral consortium and blue sky* (Vol. 1831, pp. 63–68). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-36336-8_9.

Jamet, H., Shrestha, Y. R., & Vlachos, M. (2024). Difficulty estimation and simplification of French text using LLMs. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 395–404). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_34.

Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., & Kirschner, P. A. (2021). What multimodal data can tell us about the students' regulation of their learning process? *Learning and Instruction, 72*, Article 101203. https://doi.org/10.1016/j.learninstruc.2019.04.004

Järvelä, S., Nguyen, A., & Hadwin, A. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology, 54*(5), 1057–1076. https://doi.org/10.1111/bjet.13325

Järvelä, S., Zhao, G., Heikkilä, J., Järvenoja, H., Mikkonen, K., & Kaleva, S. (2023). Hybrid intelligence—Human–AI co-evolution and learning in multirealities (HI). In *Proceedings of the 2nd international conference on hybrid human–artificial intelligence* (pp. 392–394). IOS Press.

Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management, 8*(4), Article 100078. https://doi.org/10.1016/j.dim.2024.100078

Jin, F., Maheshi, B., Martinez-Maldonado, R., Gašević, D., & Tsai, Y.-S. (2024). Scaffolding feedback literacy: Designing a feedback analytics tool with students. *Journal of Learning Analytics, 11*(2), 123–137. https://doi.org/10.18608/jla.2024.8339

Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers and Education: Artificial Intelligence, 8*, Article 100348. https://doi.org/10.1016/j.caeai.2024.100348

Jin, Y., & Yu, J. (2024). Optimizing mentor-student communication using LLM-based automated labeling information states. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 284–288). https://doi.org/10.1145/3657604.3664691

Johnson, W. L. (2024). How to harness generative AI to accelerate human learning. *International Journal of Artificial Intelligence in Education, 34*(3), 1287–1291. https://doi.org/10.1007/s40593-023-00367-w

Johnson, B. G., Dittel, J. S., & Van Campenhout, R. (2024). Investigating student ratings with features of automatically generated questions: A large-scale analysis using data from natural learning contexts. https://doi.org/10.5281/ZENODO.12729796.

Johnson, B. G., Van Campenhout, R., Jerome, B., Castro, M. F., Bistolfi, R., & Dittel, J. S. (2024). Automatic question generation for spanish textbooks: Evaluating spanish questions generated with the parallel construction method. *International Journal of Artificial Intelligence in Education, 35*(3), 1044–1063. https://doi.org/10.1007/s40593-024-00394-1

Kakar, S., Maiti, P., Taneja, K., Nandula, A., Nguyen, G., Zhao, A., Nandan, V., & Goel, A. (2024). Jill Watson: Scaling and deploying an AI conversational agent in online classrooms. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 78–90). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_7.

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human-Computer Interaction, 40*(2), 497–514. https://doi.org/10.1080/10447318.2022.2151730

Kim, J. (2024). Leading teachers' perspective on teacher-AI collaboration in education. *Education and Information Technologies, 29*(7), 8693–8724. https://doi.org/10.1007/s10639-023-12109-5

Kirkley, A. (2024). Identifying hubs in directed networks. *Physical Review E, 109*(3), Article 034310.

Kumar, H., Xiao, R., Lawson, B., Musabirov, I., Shi, J., Wang, X., Luo, H., Williams, J. J., Rafferty, A. N., Stamper, J., & Liut, M. (2024). Supporting self-reflection at scale with large language models: Insights from randomized field experiments in classrooms. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 86–97). https://doi.org/10.1145/3657604.3662042

Lai, C. Y., Cheung, K. Y., & Chan, C. S. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. *Computers and Education: Artificial Intelligence, 5*, Article 100178. https://doi.org/10.1016/j.caeai.2023.100178

Lämsä, J., Edwards, J., Haataja, E., Sobocinski, M., Peña, P., Nguyen, A., & Järvelä, S. (2024). Learners' linguistic alignment and physiological synchrony: Identifying trigger events that invite socially shared regulation of learning. *Journal of Learning Analytics*, 1–18. https://doi.org/10.18608/jla.2024.8287

Li, H., Cheng, F., Wang, G., Cai, Z., & Graesser, A. (2024). Impact of conversational agent language and text structure on student language. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 217–231). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_17.

Li, H., Guo, R., Li, C., & Xing, W. (2024). Automated quality assessment of multimodal mathematical stories generated by generative artificial intelligence. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 110–121). https://doi.org/10.1145/3657604.3662029

Li, Z., Jensen, M. T., Nolte, A., & Spikol, D. (2024). Field report for platform mBox: Designing an open MMLA platform. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 785–791). https://doi.org/10.1145/3636555.3636872

Li, H., Lee, S., & Botelho, A. F. (2024). This paper was written with the help of ChatGPT: Exploring the consequences of AI-driven academic writing on scholarly practices. https://doi.org/10.5281/ZENODO.12729880.

Li, Y., Raković, M., Dai, W., Lin, J., Khosravi, H., Galbraith, K., Lyons, K., Gašević, D., & Chen, G. (2023). Are deeper reflectors better goal-setters? AI-empowered analytics of reflective writing in pharmaceutical education. *Computers and Education: Artificial Intelligence, 5*, Article 100157. https://doi.org/10.1016/j.caeai.2023.100157

Lifshits, I., & Rosenberg, D. (2024). Artificial intelligence in nursing education: A scoping review. *Nurse Education in Practice, 80*, Article 104148. https://doi.org/10.1016/j.nepr.2024.104148

Lin, M. P.-C., & Chang, D. (2023). CHAT-ACTS: A pedagogical framework for personalized chatbot to enhance active learning and self-regulated learning. *Computers and Education: Artificial Intelligence, 5*, Article 100167. https://doi.org/10.1016/j.caeai.2023.100167

Lin, J., Chen, E., Gurung, A., & Koedinger, K. R. (2024). MuFIN: A framework for automating multimodal feedback generation using generative artificial intelligence. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 550–552). https://doi.org/10.1145/3657604.3664720

Litovkin, D., Anikin, A., Kulyukin, K., & Sychev, O. (2022). Intelligent tutor for designing function interface in a programming language. In S. Crossley, & E. Popescu (Eds.), *Intelligent tutoring systems* (Vol 13284, pp. 293–302). Springer International Publishing. https://doi.org/10.1007/978-3-031-09680-8_27.

Ma, Y., Celepkolu, M., & Boyer, K. E. (2022). Detecting impasse during collaborative problem solving with multimodal learning analytics. In *LAK22: 12th international learning analytics and knowledge conference* (pp. 45–55). https://doi.org/10.1145/3506860.3506865

Mangaroska, K., Sharma, K., Gašević, D., & Giannakos, M. (2020). Multimodal learning analytics to inform learning design: Lessons learned from computing education. *Journal of Learning Analytics, 7*(3), 79–97. https://doi.org/10.18608/jla.2020.73.7

Marzano, D. (2025). Generative artificial intelligence (GAI) in teaching and learning processes at the K-12 level: A systematic review. *Technology, Knowledge and Learning.* https://doi.org/10.1007/s10758-025-09853-7

Matos, T., Santos, W., Zdravevski, E., Coelho, P. J., Pires, I. M., & Madeira, F. (2025). A systematic review of artificial intelligence applications in education: Emerging trends and challenges. *Decision Analytics Journal, 15*, Article 100571. https://doi.org/10.1016/j.dajour.2025.100571

Meaney, M., & Fikes, T. (2022). Adding a demographic lens to cluster analysis of participants in entry-level massive open online courses (MOOCS). In *Proceedings of the ninth ACM conference on learning @ scale* (pp. 355–359). https://doi.org/10.1145/3491140.3528306

Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education, 57*(4), 632–645. https://doi.org/10.1111/ejed.12527

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: A state of the art. *Artificial Intelligence Review, 56*(4), 3005–3054. https://doi.org/10.1007/s10462-022-10246-w

Mustafa, M. Y., Tlili, A., Lampropoulos, G., Huang, R., Jandrić, P., Zhao, J., Salha, S., Xu, L., Panda, S., Kinshuk López-Pernas, S., & Saqr, M. (2024). A systematic review of literature reviews on artificial intelligence in education (AIED): A roadmap to a future research agenda. *Smart Learning Environments, 11*(1), 59. https://doi.org/10.1186/s40561-024-00350-5

Myint, P. Y. W., Lo, S. L., & Zhang, Y. (2024). Harnessing the power of AI-instructor collaborative grading approach: Topic-based effective grading for semi open-ended multipart questions. *Computers and Education: Artificial Intelligence, 7*, Article 100339. https://doi.org/10.1016/j.caeai.2024.100339

Naik, A., Yin, J. R., Kamath, A., Ma, Q., Wu, S. T., Murray, C., Bogart, C., Sakr, M., & Rose, C. P. (2024). Generating situated reflection triggers about alternative solution paths: A case study of generative AI for computer-supported collaborative learning. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol 14829, pp. 46–59). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64302-6_4.

Ndukwe, I. G., Amadi, C. E., Nkomo, L. M., & Daniel, B. K. (2020). Automatic grading system using sentence-BERT network. In I. I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial intelligence in education* (Vol 12164, pp. 224–227). Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_41.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review, 45*(2), 167–256. https://doi.org/10.1137/S003614450342480

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences, 103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Ng, J. T. D., Hu, X., & Que, Y. (2022). Towards multi-modal evaluation of eye-tracked virtual heritage environment. In *LAK22: 12th international learning analytics and knowledge conference* (pp. 451–457). https://doi.org/10.1145/3506860.3506881

Ng, J. T. D., Liu, Y., Chui, D. S. Y., Man, J. C. H., & Hu, X. (2023). Leveraging LMS logs to analyze self-regulated learning behaviors in a maker-based course. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 670–676). https://doi.org/10.1145/3576050.3576111

Nguyen, M. H., Tschiatschek, S., & Singla, A. (2024). Large language models for in-context student modeling: Synthesizing student's behavior in visual programming. https://doi.org/10.5281/ZENODO.12729830.

Nikou, S. A., Guliya, A., Van Verma, S., & Chang, M. (2024). A generative artificial intelligence empowered chatbot: System usability and student teachers' experience. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 330–340). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_27.

Nishida, N., Nozaki, H., & Shizuki, B. (2022). Laugh at your own pace: Basic performance evaluation of language learning assistance by adjustment of video playback speeds based on laughter detection. *Proceedings of the ninth ACM conference on learning @ scale.* https://doi.org/10.1145/3491140.3528299

Ouhaichi, H., Spikol, D., & Vogel, B. (2023). Research trends in multimodal learning analytics: A systematic mapping study. *Computers and Education: Artificial Intelligence, 4*, Article 100136. https://doi.org/10.1016/j.caeai.2023.100136

Paaß, G., & Giesselbach, S. (2023). Foundation models for speech, images, videos, and control. In G. Paaß, & S. Giesselbach (Eds.), *Foundation models for natural language processing* (pp. 313–382). Springer International Publishing. https://doi.org/10.1007/978-3-031-23190-2_7.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). *Artificial intelligence in education: Challenges and opportunities for sustainable development*.

Puranam, P. (2021). Human–AI collaborative decision-making as an organization design problem. *Journal of Organ Dysfunction, 10*(2), 75–80. https://doi.org/10.1007/s41469-021-00095-2

Quick, J. D., Motz, B., & Morrone, A. (2023). Lost in translation: Determining the generalizability of temporal models across course contexts. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 273–283). https://doi.org/10.1145/3576050.3576092

Radhakrishnan, S., Erbis, S., Isaacs, J. A., & Kamarthi, S. (2017). Novel keyword co-occurrence network-based methods to foster systematic reviews of scientific literature. *PLoS One, 12*(3), Article e0172778. https://doi.org/10.1371/journal.pone.0172778

Rajarathinam, R. J., Palaguachi, C., & Kang, J. (2024). Enhancing multimodal learning analytics: A comparative study of facial features capture using traditional vs 360-degree cameras in collaborative learning. https://doi.org/10.5281/ZENODO.12729882.

Ravasz, E., & Barabási, A.-L. (2003). Hierarchical organization in complex networks. *Physical Review E, 67*(2), Article 026112. https://doi.org/10.1103/PhysRevE.67.026112

Rodrigues, L., Dwan Pereira, F., Cabral, L., Gašević, D., Ramalho, G., & Ferreira Mello, R. (2024). Assessing the quality of automatic-generated short answers using GPT-4. *Computers and Education: Artificial Intelligence, 7*, Article 100248. https://doi.org/10.1016/j.caeai.2024.100248

Rodrigues, L., Pereira, F. D., Cabral, L., Ramalho, G., Gasevic, D., & Mello, R. F. (2024). Can GPT4 answer educational tests? Empirical analysis of answer quality based on question complexity and difficulty. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol 14829, pp. 192–205). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-64302-6_14.

Salman, A., & Alexandron, G. (2024). The digital fingerprint of learner behavior: Empirical evidence for individuality in learning using deep learning. *Computers and Education: Artificial Intelligence, 7*, Article 100322. https://doi.org/10.1016/j.caeai.2024.100322

Sankaranarayanan, S., Kandimalla, S. R., Bogart, C., Murray, R. C., Hilton, M., Sakr, M., & Rosé, C. (2021). Combining collaborative reflection based on worked-out examples with problem-solving practice: Designing collaborative programming projects for learning at scale. In *Proceedings of the eighth ACM conference on learning @ scale* (pp. 255–258). https://doi.org/10.1145/3430895.3460152

Schmucker, R., Xia, M., Azaria, A., & Mitchell, T. (2024). Ruffle&Riley: From lesson text to conversational tutoring. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 547–549). https://doi.org/10.1145/3657604.3664719

Schneider, B., & Sung, G. (2024). Is seeing the instructor's face or gaze in online videos helpful for learning? *Journal of Learning Analytics, 11*(3), 210–223. https://doi.org/10.18608/jla.2024.8235

Seo, J. H., Chaudhury, R., Oh, J.-H., Kicklighter, C., Arguello, T., Wells-Beede, E., & Weston, C. (2023). Development of virtual reality SBIRT skill training with conversational AI in nursing education. In N. Wang, G. Rebolledo-Mendez, N. Matsuda, O. C. Santos, & V. Dimitrova (Eds.), *Artificial intelligence in education* (Vol 13916, pp. 701–707). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-36272-9_59.

Shahriar, T., & Matsuda, N. (2024). "I Am Confused! How to Differentiate Between…?" adaptive Follow-Up questions facilitate tutor learning with effective time-on-task. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol. 14830, pp. 17–30). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64299-9_2.

Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology, 51*(5), 1450–1484. https://doi.org/10.1111/bjet.12993

Sheel, S., Anastasopoulos, I., & Pardos, Z. A. (2024). Comparing authoring experiences with spreadsheet interfaces vs GUIS. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 598–607). https://doi.org/10.1145/3636555.3636919

Smerdon, D. (2024). AI in essay-based assessment: Student adoption, usage, and performance. *Computers and Education: Artificial Intelligence, 7*, Article 100288. https://doi.org/10.1016/j.caeai.2024.100288

Smith, D. H., Denny, P., & Fowler, M. (2024). Prompting for comprehension: Exploring the intersection of explain in plain English questions and prompt writing. In

Proceedings of the eleventh ACM conference on learning @ scale (pp. 39–50). https://doi.org/10.1145/3657604.3662039

Sonkar, S., Ni, K., Tran Lu, L., Kincaid, K., Hutchinson, J. S., & Baraniuk, R. G. (2024). Automated long answer grading with RiceChem dataset. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol 14829, pp. 163–176). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-64302-6_12.

Sosnowski, T., Abuazizeh, M., Kirste, T., & Yordanova, K. (2023). Development of a conversational agent for tutoring nursing students to interact with patients. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol 13891, pp. 171–182). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_15.

Southworth, J., Migliaccio, K., Glover, J., Glover, J., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence, 4*, Article 100127. https://doi.org/10.1016/j.caeai.2023.100127

Su, H. N., & Lee, P. C. (2010). Mapping knowledge structure by keyword co-occurrence: A first look at journal papers in technology foresight. *Scientometrics, 85*(1), 65–79. https://doi.org/10.1007/s11192-010-0259-8

Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence, 4*, Article 100124. https://doi.org/10.1016/j.caeai.2023.100124

Sun, C., Major, L., Daltry, R., Moustafa, N., & Friedberg, A. (2024). Teacher-AI collaboration in content recommendation for digital personalised learning among pre-primary learners in Kenya. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 346–350). https://doi.org/10.1145/3657604.3664662

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence, 8*, Article 100355. https://doi.org/10.1016/j.caeai.2024.100355

Tchio, G. C. T., Nkambou, R., Tato, A. A. N., & Psyché, V. (2024). Towards cognitive coaching in aircraft piloting tasks: Building an ACT-R synthetic pilot integrating an ontological reference model to assist the pilot and manage deviations. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 202–216). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_16.

Thomas, D. R., Lin, J., Bhushan, S., Abboud, R., Gatz, E., Gupta, S., & Koedinger, K. R. (2024). Learning and AI evaluation of tutors responding to students engaging in negative self-talk. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 481–485). https://doi.org/10.1145/3657604.3664700

Thomas, C., Puneeth Sarma, K. A. V., Swaroop Gajula, S., & Jayagopi, D. B. (2022). Automatic prediction of presentation style and student engagement from videos. *Computers and Education: Artificial Intelligence, 3*, Article 100079. https://doi.org/10.1016/j.caeai.2022.100079

Topali, P., Haelermans, C., Molenaar, I., & Segers, E. (2025). Pedagogical considerations in the automation era: A systematic literature review of AIEd in K-12 authentic settings. *British Educational Research Journal*. https://doi.org/10.1002/berj.4200. berj.4200.

Valle Torre, M., Tan, E., & Hauff, C. (2020). edX log data analysis made easy: Introducing ELAT: An open-source, privacy-aware and browser-based edX log data analysis tool. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 502–511). https://doi.org/10.1145/3375462.3375510

Van Campenhout, R., Clark, M., Jerome, B., Dittel, J. S., & Johnson, B. G. (2023). Advancing intelligent textbooks with automatically generated practice: A large-scale analysis of student data. In *5th workshop on intelligent textbooks. The 24th international conference on artificial intelligence in education*. https://intextbooks.science.uu.nl/workshop2023/fi.

Van Campenhout, R., Kimball, M., Clark, M., Dittel, J. S., Jerome, B., & Johnson, B. G. (2024). An investigation of automatically generated feedback on student behavior and learning. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 850–856). https://doi.org/10.1145/3636555.3636901

Vasić, D., Žitko, B., Grubišić, A., & Gašpar, A. (2023). KEMMRL: Knowledge extraction model for morphologically rich languages. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 220–232). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_19.

Wambsganss, T., Benke, I., Maedche, A., Koedinger, K., & Käser, T. (2025). Evaluating the impact of learner control and interactivity in conversational tutoring systems for persuasive writing. *International Journal of Artificial Intelligence in Education, 35*(2), 791–822. https://doi.org/10.1007/s40593-024-00409-x

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence, 7*, Article 100326. https://doi.org/10.1016/j.caeai.2024.100326

Wang, Q., Gao, Y., & Wang, X. (2025). Exploring engagement, self-efficacy, and anxiety in large language model EFL learning: A latent profile analysis of Chinese university students. *International Journal of Human-Computer Interaction, 41*(12), 7815–7824. https://doi.org/10.1080/10447318.2024.2400403

Wang, Y., Guo, S., Ling, L., & Tan, C. W. (2024). Nemobot: Crafting strategic gaming LLM agents for K-12 AI education. In *Proceedings of the eleventh ACM conference on learning @ scale* (pp. 393–397). https://doi.org/10.1145/3657604.3664671

Wang, J., Ivrissimtzis, I., Li, Z., Zhou, Y., & Shi, L. (2023). User-defined hand gesture interface to improve user experience of learning American sign language. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 479–490). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_43.

Wang, Z., Ng, J. T. D., Que, Y., & Hu, X. (2024). Unveiling synchrony of learners' multimodal data in collaborative maker activities. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 922–928). https://doi.org/10.1145/3636555.3636935

Wang, Y., & Xue, L. (2024). Using AI-driven chatbots to foster Chinese EFL students' academic engagement: An intervention study. *Computers in Human Behavior, 159*, Article 108353. https://doi.org/10.1016/j.chb.2024.108353

Weng, X., Xia, Q., Ahmad, Z., & Chiu, T. K. F. (2024). Personality traits for self-regulated learning with generative artificial intelligence: The case of ChatGPT. *Computers and Education: Artificial Intelligence, 7*, Article 100315. https://doi.org/10.1016/j.caeai.2024.100315

Wu, H., & Wang, Y. (2025). Disclosing Chinese college students' flow experience in GenAI-assisted informal digital learning of English: A self-determination theory perspective. *Learning and Motivation, 90*, Article 102134. https://doi.org/10.1016/j.lmot.2025.102134

Xu, W., & Ouyang, F. (2022). The application of AI technologies in STEM education: A systematic review from 2011 to 2021. *International Journal of STEM Education, 9*(1), 59. https://doi.org/10.1186/s40594-022-00377-5

Xu, L., Pardos, Z. A., & Pai, A. (2023). Convincing the expert: Reducing algorithm aversion in administrative higher education decision-making. In *Proceedings of the tenth ACM conference on learning @ scale* (pp. 215–225). https://doi.org/10.1145/3573051.3593378

Yan, L., Echeverria, V., Jin, Y., Fernandez-Nieto, G., Zhao, L., Li, X., Alfredo, R., Swiecki, Z., Gašević, D., & Martinez-Maldonado, R. (2024c). Evidence-based multimodal learning analytics for feedback and reflection in collaborative learning. *British Journal of Educational Technology, 55*(5), 1900–1925. https://doi.org/10.1111/bjet.13498

Yan, H., Lin, F., & Kinshuk. (2024a). An ai-learner shared control model design for adaptive practicing. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (Vol 14798, pp. 272–280). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-63028-6_21.

Yan, L., Martinez-Maldonado, R., & Gasevic, D. (2024d). Generative artificial intelligence in learning analytics: Contextualising opportunities and challenges through the learning analytics cycle. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 101–111). https://doi.org/10.1145/3636555.3636856

Yan, L., Zhao, L., Echeverria, V., Jin, Y., Alfredo, R., Li, X., Gaševi`c, D., & Martinez-Maldonado, R. (2024e). VizChat: Enhancing learning analytics dashboards with contextualised explanations using multimodal generative AI chatbots. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial intelligence in education* (Vol. 14830, pp. 180–193). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64299-9_13.

Yan, L., Zhao, L., Echeverria, V., Jin, Y., Alfredo, R., Li, X., … Martinez-Maldonado, R. (2024b). VizChat: Enhancing learning analytics dashboards with contextualised explanations using multimodal generative AI chatbots. July. In *International conference on artificial intelligence in education* (pp. 180–193). Cham: Springer Nature Switzerland.

Yang, Y., Dong, Y., & Chawla, N. V. (2014). Predicting node degree centrality with the node prominence profile. *Scientific Reports, 4*(1), 7236. https://doi.org/10.1038/srep07236

Yang, A. C. M., Lin, J.-Y., Lin, C.-Y., & Ogata, H. (2024). Enhancing python learning with PyTutor: Efficacy of a ChatGPT-Based intelligent tutoring system in programming education. *Computers and Education: Artificial Intelligence, 7*, Article 100309. https://doi.org/10.1016/j.caeai.2024.100309

Yim, I. H. Y. (2024). A critical review of teaching and learning artificial intelligence (AI) literacy: Developing an intelligence-based AI literacy framework for primary school education. *Computers and Education: Artificial Intelligence, 7*, Article 100319. https://doi.org/10.1016/j.caeai.2024.100319

Zarour, M., Ben Abdessalem, H., & Frasson, C. (2023). Distraction detection and monitoring using eye tracking in virtual reality. In C. Frasson, P. Mylonas, & C. Troussas (Eds.), *Augmented intelligence and intelligent tutoring systems* (Vol. 13891, pp. 491–503). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-32883-1_44.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity, 2021*(1), Article 8812542. https://doi.org/10.1155/2021/8812542

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence, 2*, Article 100025. https://doi.org/10.1016/j.caeai.2021.100025

Zhang, J., Borchers, C., Aleven, V., & Baker, R. S. (2024). Using large language models to detect self-regulated learning in think-aloud protocols. In P. Benjamin, & D. E. Carrie (Eds.), *Proceedings of the 17th international conference on educational data mining.* International Educational Data Mining Society. https://doi.org/10.5281/ZENODO.12729790.

Zhang, H., Perry, A., & Lee, I. (2025). Developing and validating the artificial intelligence literacy concept inventory: An instrument to assess artificial intelligence literacy among middle school students. *International Journal of Artificial Intelligence in Education, 35*(1), 398–438. https://doi.org/10.1007/s40593-024-00398-x