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Artificial intelligence in education: mapping research trends, engagement and cognitive disengagement with evidence from global and Asian contexts

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Abstract

Purpose – This study aims to examine the intellectual structure, evolution and emerging trends of artificial intelligence (AI) in education, with a specific focus on student engagement and cognitive disengagement, within a rapidly expanding and technology-driven research landscape.

Design/methodology/approach – A bibliometric analysis was conducted using the Scopus database, covering journal articles published between 2015 and 2026. A total of 3,861 publications were analyzed using performance analysis and science mapping techniques. Tools such as Bibliometrix and R software were employed to examine publication trends, citation patterns, keyword co-occurrence, thematic structures, and disengagement-related research patterns.

Findings – The results reveal significant growth in AI-in-education research, particularly after 2023, driven by the emergence of generative AI technologies such as ChatGPT. Thematic analysis indicates a shift from technology-oriented research toward learner-centered constructs, with student engagement acting as a key bridging concept. It is important to distinguish two related but separate claims; while a substantial proportion of the corpus (61–73% annually) addresses constructs adjacent to disengagement such as motivation, attention, and engagement cognitive disengagement as an independent, explicitly labelled construct receives comparatively limited direct attention (2.2% of the disengagement sub-corpus). This distinction reconciles the apparent tension between the high proportion of disengagement-adjacent literature and the claim that disengagement remains underexplored as a standalone variable. The findings also highlight a geographically concentrated research landscape, with strong contributions from Asian countries, particularly China and the Asia-Pacific region.

Research limitations/implications – The study is limited to Scopus-indexed journal articles and English-language publications. Future research should explore cognitive disengagement through empirical and longitudinal studies, particularly in diverse educational and regional contexts, including underrepresented areas within Asia.

Practical implications – The findings emphasize the need for educators and policymakers to adopt a balanced approach to AI integration, ensuring that technological advancement does not compromise critical thinking, attention, and deep learning.

Originality/value – This study contributes to the literature by integrating bibliometric mapping with a disengagement-focused perspective, offering a novel understanding of how AI technologies influence both engagement and cognitive disengagement in education.

Keywords Artificial intelligence, Generative AI, ChatGPT, Student engagement, Cognitive disengagement, Higher education, Learning analytics, Bibliometric analysis, Asia-Pacific, Educational technology

Paper type Literature review

1. Introduction

Artificial intelligence (AI) has moved from being a supporting digital tool to becoming a major force shaping educational practice, curriculum delivery, and learning assessment. Recent reviews show that AI in education now covers adaptive learning, intelligent assessment, profiling and prediction, and emerging educational products, while also remaining a highly multidisciplinary field with several still underexplored directions (Wang *et al.*, 2024). At the same time, bibliometric mapping of recent generative AI scholarship shows a sharp rise in

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publications since 2022, with strong concentration around higher education, ethics, writing support, and assessment, indicating that AI is no longer a peripheral topic in education research but a central one (Lachheb *et al.*, 2025).

The acceleration of generative AI, particularly ChatGPT, has further intensified this shift. Recent studies report that ChatGPT can support personalized tutoring, programming and technical assistance, and content generation, but the same literature also identifies concerns such as overreliance, reduced critical thinking, and academic dishonesty (Lee *et al.*, 2025; Heung and Chiu, 2025). Broader systematic reviews similarly show that AI in education is expanding rapidly and that, alongside benefits such as improved learning outcomes, personalized instruction, and increased motivation, researchers are also increasingly concerned about ethical use, teacher resistance, and digital dependency (Jafari *et al.*, 2025; Garzón *et al.*, 2025).

A growing body of cognitive psychology research provides important theoretical context for these concerns. Studies on automation bias the tendency to over-rely on automated systems even when they produce errors suggest that excessive AI use in learning environments may reduce learners' independent reasoning and critical evaluation skills (Parasuraman and Riley, 1997; Skitka *et al.*, 1999). More recently, AI-specific research has documented over-reliance effects in educational settings, where learners who habitually use AI-generated answers demonstrate shallower knowledge retention and reduced metacognitive monitoring (Kasneci *et al.*, 2023).

This makes student engagement a crucial lens through which to examine the educational value of AI. The recent review by Lee and Kwon (2024) shows that ChatGPT-related learning can produce both engagement and disengagement, including cognitive disengagement through reduced critical thinking and overreliance. In the same direction, Heung and Chiu (2025) found that ChatGPT can strengthen behavioral, cognitive, and emotional engagement, but also carries the risk of disengagement when learners depend too heavily on machine-generated support. Research from Asian educational contexts further illuminates these dynamics. Studies from China, the most productive country in this corpus, indicate that AI adoption in higher education settings is often framed around performance optimisation and assessment efficiency rather than deeper cognitive engagement, raising questions about whether the regional concentration of AI-education research reflects particular pedagogical philosophies that may differ from Western learner-centered traditions (Wang *et al.*, 2024; Rosa and Yokomizo, 2026).

In higher education, the discussion is moving beyond efficiency toward the quality of learner participation, inclusion, ethics, and AI literacy. A recent bibliometric synthesis of AI in higher education highlights these themes as central concerns, showing that the literature is now examining how AI relates to educational equity, large language model ethics, translation tools, and academic standards (Lachheb *et al.*, 2025). Because the field is expanding quickly and is distributed across multiple journals, themes, and disciplines, a bibliometric approach is especially appropriate. Recent Scopus- and Web of Science-based mapping studies confirm that bibliometric analysis helps identify research gaps, co-occurrence structures, and geographic patterns in AI in education, making it a suitable method for tracing both growth and conceptual development in this area (Rosa and Yokomizo, 2026).

While a substantial proportion of the AI-in-education corpus touches on constructs adjacent to disengagement such as motivation loss, reduced attention, and overreliance very few studies treat disengagement itself as a primary independent construct under direct investigation. This study therefore argues that disengagement is simultaneously prevalent as a contextual concern and underexplored as a focused research object. These are complementary rather than contradictory observations, and this distinction shapes the analytical framing of the present study throughout.

Accordingly, the present study focuses on the last ten years of literature to map the intellectual structure of AI in education and to understand how the field connects AI tools with student engagement and cognitive disengagement. By doing so, the study aims to move beyond a purely technological reading of AI and instead examine its educational meaning in terms of attention, involvement, critical thinking, and learning depth. The remainder of the paper is organised as follows: Section 2 presents the methodology, Section 3 reports results, Section 4 provides the discussion, Section 5 outlines implications, and Section 6 offers conclusions.

2. Methodology

2.1 Theoretical framework

This study is anchored in three complementary theoretical frameworks that inform both the analytical design and the interpretation of findings. First, Engagement Theory (Kearsley and Shneiderman, 1998) posits that meaningful learning requires active participation, collaboration, and real-world relevance a lens through which the evolution from technology-centric to learner-centered research themes is interpreted. Second, Self-Determination Theory (Reeve, 2012) focuses on the psychological needs of autonomy, competence, and relatedness as drivers of motivated learning relevant because generative AI tools may simultaneously enhance perceived autonomy while reducing intrinsic cognitive effort. Third, Cognitive Load Theory (Kirschner, 2002) distinguishes between extraneous, intrinsic, and germane cognitive load critical for understanding how AI may reduce surface cognitive effort while potentially diminishing the deeper germane processing essential for knowledge construction. Together, these frameworks provide the multi-dimensional theoretical scaffolding through which the bibliometric patterns in this study are interpreted.

2.2 Research design

This study adopts a bibliometric research design to examine the evolution, structure, and thematic development of research on artificial intelligence in education, with particular attention to engagement- and disengagement-related constructs. Bibliometric analysis is well suited to this topic because it allows researchers to map performance patterns and knowledge structures in a large, fast-growing, and interdisciplinary literature (Wang, 2018). Following established bibliometric guidance, the study combines performance analysis and science mapping to capture both publication impact and conceptual relationships within the field (Donthu *et al*., 2021; Aria and Cuccurullo, 2017). Scopus was selected as the data source because it is a multidisciplinary abstract and citation database with broad journal coverage and structured metadata that supports reliable bibliometric retrieval and analysis.

2.3 Search strategy and data collection

The search strategy used the TITLE-ABS-KEY ((“artificial intelligence” OR “machine learning” OR “deep learning” OR “generative AI” OR “generative artificial intelligence” OR ChatGPT OR “large language model*” OR LLM* OR “intelligent tutoring system*” OR “learning analytics” OR “adaptive learning”) AND (educat* OR learn* OR teach* OR student* OR classroom* OR school* OR universit* OR “higher education”) AND ((disengag* W/3 student*) OR (engag* W/3 student*) OR (“cognitive load” W/3 learn*) OR (motivation W/3 student*) OR (attention W/3 student*))) AND PUBYEAR >2014 AND PUBYEAR <2027 AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (SUBJAREA, “SOCI”) OR LIMIT-TO (SUBJAREA, “COMP”) OR LIMIT-TO (SUBJAREA, “PSYC”) OR LIMIT-TO (SUBJAREA, “BUSI”) OR LIMIT-TO (SUBJAREA, “ECON”)) AND (LIMIT-TO (LANGUAGE, “English”)).

The inclusion of engagement and disengagement proximity terms in the search query intentionally focuses the retrieved corpus on AI-in-education literature that has some connection to engagement or disengagement constructs. This is a deliberate scoping decision aligned with the study’s research focus rather than a bias or error. It means the 3,861-

publication corpus should be understood as a focused subset of the broader AI-in-education literature rather than an exhaustive census of that literature.

It is also important to note that throughout this study, conclusions about generative AI specifically are drawn only from keywords explicitly labelled "generative AI," "ChatGPT," or "generative artificial intelligence." The broader keyword "artificial intelligence" is treated as an umbrella term encompassing both traditional and generative AI approaches. These terms are not used interchangeably, and interpretive claims are calibrated accordingly.

The search was restricted to journal articles, English-language publications, and the subject areas SOCI, COMP, PSYC, BUSI, and ECON. According to the file, the initial search returned more than 9,000 records, which were refined to a final dataset of 3,861 publications after applying the subject-area, source-type, and language filters.

2.4 Data extraction and analytical procedure

The study extracted the following variables from Scopus: title, authors, year, source title, abstract, author keywords, indexed keywords, citations, affiliations, country, subject area, references, DOI, and document type. These fields are standard inputs for bibliometric analysis (Donthu *et al*., 2021; Aria and Cuccurullo, 2017).

The analytical procedure followed a multi-stage workflow: (1) annual publication trend analysis; (2) annual citation trend analysis; (3) keyword co-occurrence analysis to identify dominant themes and bridging concepts; (4) top-author, top-journal, top-country, and top-institution analyses; (5) Bradford's law for journal concentration analysis (Naranan, 1970); (6) Lotka's law for author productivity patterns (Ahmad *et al*., 2021); and (7) a dedicated disengagement annual trend analysis. For mapping and visualisation, Bibliometrix/ Biblioshiny and VOSviewer were used. VOSviewer network files (.vos and .json) are available from the corresponding author upon request.

3. Results and discussions

3.1 Publication trend of AI in education

Table 1 and Figure 1 indicate a clear upward trajectory in AI-in-education research from 2015 to 2026, with three distinct phases. Between 2015 and 2020, publications grew gradually from 41 to 103, reflecting an exploratory stage focused on foundational AI applications in education. From 2021 to 2023, output increased more rapidly (157–320), signalling consolidation and broader adoption of digital and AI-enabled learning environments. A sharp surge is observed from 2023 to 2025, with publications rising from 320 to 1,600. The lower count in 2026 (420) is likely due to partial-year data rather than a decline in research activity.

What this growth trajectory reveals about the field is more significant than the numbers alone suggest. The exponential increase after 2023 coincides precisely with the public release and rapid adoption of ChatGPT (November 2022), confirming that generative AI not AI in

Table 1. Annual publication trend

Year	Publications	Year	Publication
2015	41	2021	157
2016	53	2022	187
2017	54	2023	320
2018	82	2024	749
2019	95	2025	1,600
2020	103	2026	420

Source(s): Scopus data base

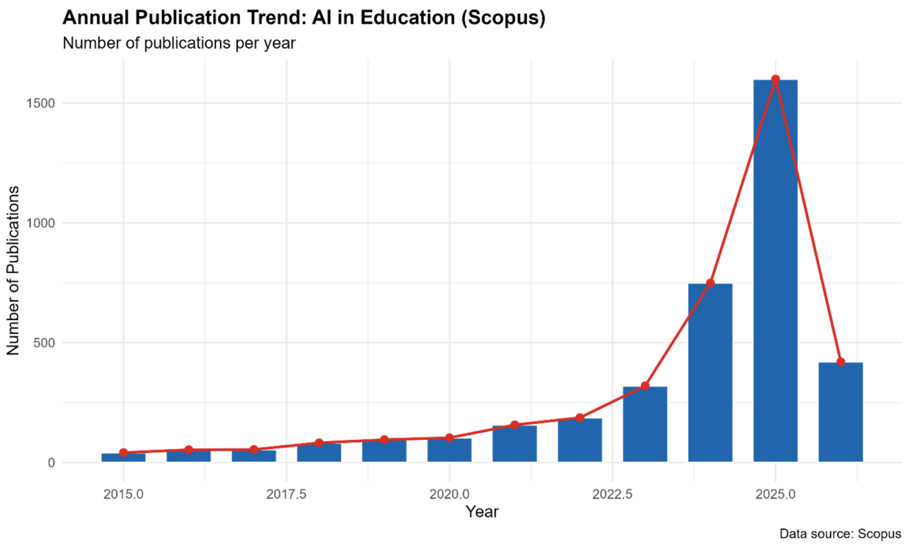

Figure 1. Annual publication trend. Source: Scopus data base

general was the specific catalyst for this acceleration. This timing is theoretically important: it suggests the field has moved from a phase of studying AI as an instructional tool to studying AI as a cognitive interlocutor that actively shapes how learners engage with content, a distinction with direct implications for the disengagement constructs examined in subsequent sections (Figure 16).

3.1.1 Keyword clusters analysis. Table 2 presents the thematic structure of AI-in-education research through keyword clustering, revealing four distinct but interconnected research streams. Cluster 1 (22 keywords) represents the technological foundation of the field, dominated by learning analytics, machine learning, deep learning, and online learning. Cluster 2, the largest with 34 keywords, forms the conceptual core, integrating artificial intelligence with higher education, student engagement, ChatGPT, and generative AI. Cluster 3 highlights learner-centric constructs, specifically learning motivation and engagement. Cluster 4 captures emerging immersive technologies such as virtual reality and augmented reality.

The analytical significance of this cluster structure lies in what it reveals about the field's conceptual organisation. The fact that student engagement (betweenness centrality = 210.39) not artificial intelligence itself functions as the most critical bridging construct across clusters (Table 3) indicates that engagement is not merely a dependent variable in this literature but the connective tissue linking technological developments to pedagogical outcomes. This has a

Table 2. Top 5 keyword clusters

Cluster	*N*_Keywords	Top_5
1	22	LEARNING ANALYTICS, MACHINE LEARNING, DEEP LEARNING, ONLINE LEARNING, E-LEARNING
2	34	ARTIFICIAL INTELLIGENCE, HIGHER EDUCATION, STUDENT ENGAGEMENT, CHATGPT, GENERATIVE AI
3	2	LEARNING MOTIVATION, LEARNING ENGAGEMENT
4	2	VIRTUAL REALITY, AUGMENTED REALITY

Source(s): Scopus data base

direct implication for how cognitive disengagement should be studied; as disengagement is the counterpart of engagement, it too should occupy a bridge position in the research architecture, yet Figure 16 shows it does not a structural gap this study highlights.

Table 3 and Figure 2 provides a detailed network-level view of the intellectual structure of AI in education by integrating keyword frequency, cluster membership, degree, and betweenness centrality. The results highlight Artificial Intelligence (frequency = 3,797; degree = 55) as the most dominant and highly connected concept, confirming its central position in the research landscape. Closely linked to this core are Higher Education and Student Engagement, both exhibiting high degree and betweenness values, with Student Engagement (betweenness = 210.39) emerging as the most critical bridging construct across thematic clusters. This indicates that engagement functions as a key integrative node connecting technological developments with pedagogical outcomes. Notably, Generative AI (betweenness = 183.81) and ChatGPT (betweenness = 114.8) demonstrate strong intermediary roles, reflecting their recent but significant influence in reshaping the field. Within Cluster 1, terms such as Learning Analytics, Machine Learning, and Deep Learning show high frequency and connectivity, representing the technological backbone of AI-driven education, while concepts like Gamification (betweenness = 113.33) and Self-regulated Learning (65.4) indicate their importance in linking technology with learner behavior. In Cluster 2, constructs such as Motivation, Educational Technology, and Personalized Learning further reinforce the shift toward learner-centric perspectives. Meanwhile, Cluster 3 (learning motivation and engagement) and Cluster 4 (virtual and augmented reality) remain smaller but conceptually distinct, representing specialized and emerging research niches. Finally, the network structure reveals a clear transition from technology-focused research toward an integrated framework where generative AI, student engagement, and learner-centered constructs act as central connectors, shaping the current and future direction of AI in education.

3.2 Annual citation trends

Table 4 and Figure 3 presents the citation dynamics of AI-in-education research, revealing distinct patterns across time. Earlier years (2015–2020) exhibit relatively high mean citation values, peaking at 60.19 in 2016, indicating that foundational studies have accumulated substantial scholarly influence over time. From 2021 onwards, total citations increase markedly, reaching a peak of 15,673 in 2024. However, mean citations decline sharply in 2024–2026, dropping to 4.96 in 2025 and 0.37 in 2026.

This citation lag pattern is not merely a statistical result but it signals that the current field is in a growth-before-consolidation phase. The high volume of recent publications has outpaced the scholarly community's capacity to evaluate and cite them, meaning that the quality and significance of post-2023 contributions remain an open empirical question. Importantly, this pattern suggests that the field's rapid expansion driven by generative AI adoption (reflected in Table 1) has not yet been accompanied by the deep critical engagement and citation accumulation that would indicate consolidation of knowledge, a concern directly relevant to the disengagement paradox discussed in Section 4.

3.3 Performance analysis by authors, journals, papers, institutions and themes

Table 5 and Figure 4 shows a concentrated authorship pattern, with Li Y (38 publications), Wang Y (33), and Hwang G-J (28) emerging as the most productive contributors. The dominance of authors with Chinese and East Asian affiliations confirms strong regional leadership, consistent with the geographic publication distribution discussed below. The findings align with Lotka's law, where a limited number of authors contribute disproportionately to the field.

The East Asian authorship concentration carries an important interpretive implication: the intellectual framing of AI in education research including how engagement and disengagement are conceptualised may reflect pedagogical assumptions rooted in

Table 3. Keyword map nodes

Keyword	Frequency	Cluster	Degree	Betweenness
Learning analytics	1964	1	30	43.57
Machine learning	1,231	1	23	48.07
Deep learning	1,203	1	19	45.4
Online learning	697	1	20	69.32
E-learning	658	1	18	29.53
Engagement	592	1	18	37.47
Active learning	510	1	13	37.64
Gamification	504	1	21	113.33
Adaptive learning	482	1	16	49.94
Self-regulated learning	395	1	16	65.4
Cognitive load	331	1	7	4.56
Blended learning	305	1	9	25.87
Educational data mining	281	1	3	0
Engineering education	273	1	8	4.75
Collaborative learning	261	1	7	19.87
Flipped classroom	249	1	8	11.33
Intelligent tutoring systems	245	1	7	2.12
Game-based learning	212	1	5	2.33
Computer vision	188	1	4	2.67
Online education	184	1	4	13.33
Experiential learning	168	1	5	25.5
Natural language processing	162	1	4	0.58
Artificial intelligence	3,797	2	55	96.95
Higher education	2038	2	40	81.77
Student engagement	2026	2	44	210.39
Chatgpt	1818	2	38	114.8
Generative ai	1,185	2	31	183.81
Educational technology	809	2	24	82.98
Motivation	714	2	25	93.32
Personalized learning	669	2	23	34.07
Education	661	2	21	46
Generative artificial intelligence	652	2	18	126.07
Artificial intelligence (ai)	524	2	10	4
Ai	445	2	11	7.5
Academic performance	335	2	11	4.9
Large language models	311	2	7	0.75
Self-efficacy	294	2	9	14.16
Learning	291	2	11	10.82
Ai in education	284	2	8	12
Ai literacy	280	2	6	2.08
Feedback	245	2	10	13.44
Self-determination theory	245	2	8	3.75
Critical thinking	239	2	6	0.5
Assessment	232	2	7	0.7
Pedagogy	227	2	9	25.57
Academic integrity	222	2	7	3.5
Technology	220	2	10	17.28
Chatbots	218	2	8	8.32
Learning outcomes	218	2	5	0
Artificial intelligence in education	210	2	4	6.95
Chatbot	207	2	5	3.42
Creativity	191	2	7	15.33
Medical education	189	2	4	0
Teaching	185	2	8	13.83
Student motivation	181	2	6	16.12

(*continued*)

Table 3. Continued

Keyword	Frequency	Cluster	Degree	Betweenness
Systematic review	166	2	5	0.33
Learning motivation	193	3	4	6
Learning engagement	193	3	4	9.38
Virtual reality	245	4	8	3.18
Augmented reality	228	4	6	1

Source(s): Scopus data base

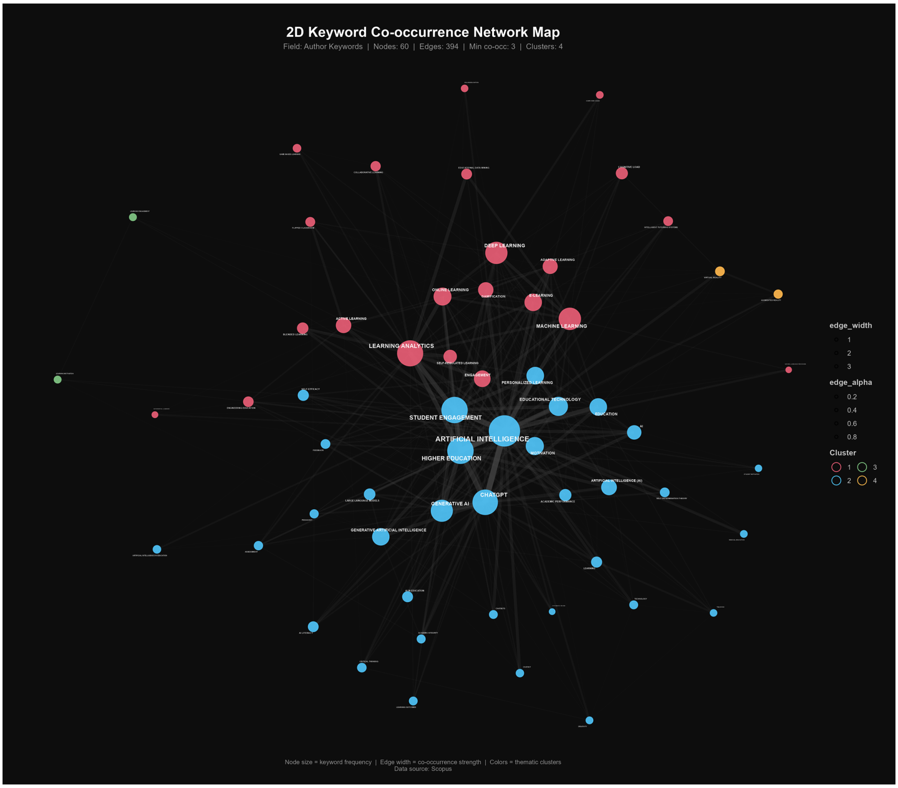

Figure 2. Keyword co-occurance map. Source: Scopus data base

Confucian educational philosophies and state-directed technology adoption policies, which differ substantially from Western constructivist traditions. Future research should examine whether findings from this corpus generalise across diverse educational cultures.

Table 6 shows that AI-in-education research is highly interdisciplinary, with Education and Information Technologies (117 publications), IEEE Access (83), and Education Sciences (82) as leading outlets, consistent with Bradford's Law's prediction of a small core group dominating publication output.

Figure 7 shows that China leads publication volume with 1,627 publications (42.1%), followed by the USA (1,252; 32.4%), Australia (437; 11.3%), India (403; 10.4%), and the

Table 4. Annual citation trend

Year	Total_ Citations	Mean_ Citations	Papers	Year	Total_ Citations	Mean_ Citations	Papers
2015	1,459	35.59	41	2021	6,078	38.71	157
2016	3,190	60.19	53	2022	5,776	30.89	187
2017	2,303	42.65	54	2023	15411	48.16	320
2018	3,028	36.93	82	2024	15673	20.93	749
2019	3,284	34.57	95	2025	7,942	4.96	1,600
2020	3,975	38.59	103	2026	154	0.37	420

Source(s): Scopus data base

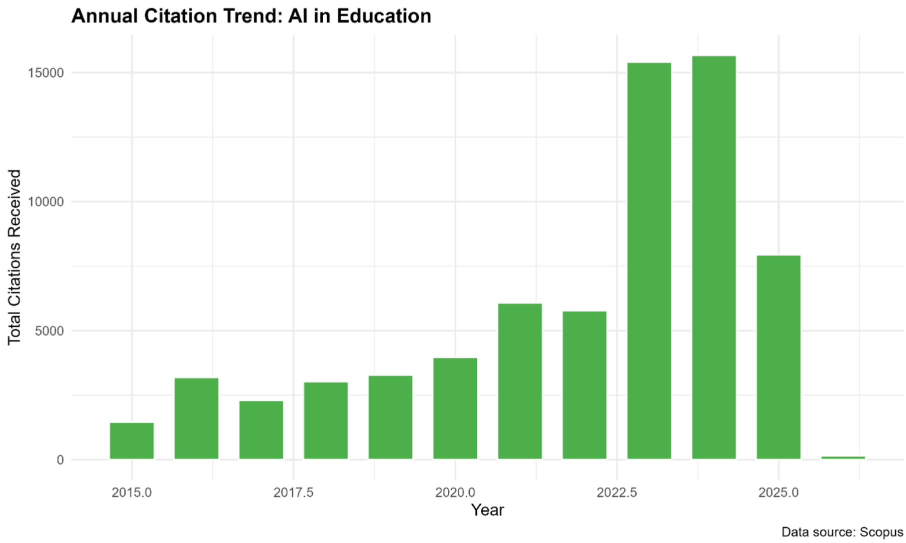

Figure 3. Annual citation trend. Source: Scopus data base

United Kingdom (345; 8.9%). Several Asian countries Saudi Arabia, Malaysia, Hong Kong, Indonesia also appear prominently.

The concentration of over 42% of publications in China alone raises a methodological concern that must be acknowledged: the findings of this bibliometric study may disproportionately reflect the research priorities, technological infrastructure, and pedagogical assumptions of Chinese higher education rather than global patterns. As noted in the methodology, the Scopus database may also under-represent non-English language publications from other Asian regions. Future research comparing Scopus and Web of Science (WoS) datasets would be valuable in assessing coverage differences, as WoS may provide better coverage of journals not indexed in Scopus.

The author co-authorship network (Figure 5) shows a highly clustered collaboration structure, with a few large nodes acting as central hubs and many smaller nodes linked around them.Li Y appears as one of the strongest connectors in the network, indicating high collaboration reach across multiple authors. Wang Y, Zhang Y, and Hwang G-J are also prominent nodes, suggesting sustained and productive research collaboration. The presence of clearly separated clusters indicates multiple research communities, rather than one fully integrated author network. The very large and dense cluster on the lower side shows the

Table 5. TOP authors

Rank	Author	Publications
1.	LI Y	38
2.	WANG Y	33
3.	HWANG G-J	28
4.	CHEN J	23
5.	ZHANG L	23
6.	ZHANG Y	23
7.	GAÅ EVIÄ† D	19
8.	CHEN Y	17
9.	LI C	17
10.	WANG J	17
11.	WANG X	17
12.	LI J	16
13.	LI S	16
14.	LIU J	16
15.	LIU Y	16
16.	WANG S	16
17.	ZHANG J	16
18.	CHIU TKF	15
19.	LI X	15
20.	LIU X	15

Source(s): Scopus data base

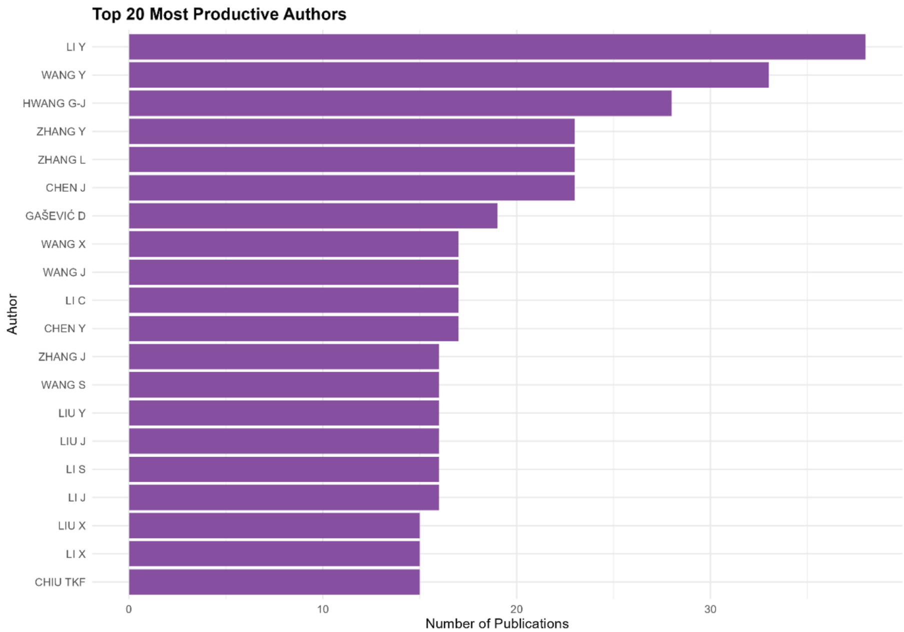

Figure 4. Top authors. Source: Scopus data base

strongest collaboration intensity, while the smaller isolated cluster at the top-right suggests a more separate community. Thus, the network suggests that AI-in-education research is driven by a few core collaborative groups, with cross-cluster links still developing.

Table 6. Top performing journals

Journal	Publications	Journal	Publications
EDUCATION AND INFORMATION TECHNOLOGIES	117	APPLIED SCIENCES (SWITZERLAND)	47
IEEE ACCESS	83	INTERNATIONAL JOURNAL OF ENGINEERING EDUCATION	42
EDUCATION SCIENCES	82	FRONTIERS IN PSYCHOLOGY	39
INTERACTIVE LEARNING ENVIRONMENTS	70	INTERNATIONAL JOURNAL OF INFORMATION AND EDUCATION TECHNOLOGY	35
BRITISH JOURNAL OF EDUCATIONAL TECHNOLOGY	60	INTERNATIONAL JOURNAL OF LEARNING TEACHING AND EDUCATIONAL RESEARCH	31
FRONTIERS IN EDUCATION	60	INTERNATIONAL JOURNAL OF INTERACTIVE MOBILE TECHNOLOGIES	30
COMPUTERS AND EDUCATION	59	BMC MEDICAL EDUCATION	29
COMPUTERS AND EDUCATION: ARTIFICIAL INTELLIGENCE	59	EDUCATIONAL TECHNOLOGY RESEARCH AND DEVELOPMENT	29
SUSTAINABILITY (SWITZERLAND)	58	COMPUTER APPLICATIONS IN ENGINEERING EDUCATION	27
JOURNAL OF COMPUTER ASSISTED LEARNING	48	EUROPEAN JOURNAL OF EDUCATION	27

Source(s): Scopus data base

China and the USA dominate AI-in-education research output, together accounting for the largest share of publications, which shows that the field is led mainly by these two research powers (Figure 6). China is the top contributor with 1,627 publications, followed by the USA with 1,252, indicating very strong national research capacity in this domain. Australia, India, and the United Kingdom form the next tier of contributors, showing that the topic has a broad international base beyond the top two countries. Several Asian countries, including Saudi Arabia, Malaysia, Hong Kong, and Indonesia, also appear prominently, suggesting strong regional interest in AI-enabled education. The distribution is clearly uneven, with a steep drop after the first few countries, which indicates a concentrated global authorship pattern. Overall, the chart shows that AI in education is a globally active field, but publication leadership is concentrated in a small number of countries.

Figure 7 (Country Collaboration Network) reveals that China and the USA serve as the primary collaboration hubs, connecting Asian, European, and Middle Eastern research communities. This network structure directly informs on geographic concentration; while output is geographically concentrated in China, the collaboration architecture shows that Chinese researchers are not working in isolation but are actively embedded in international networks. This suggests that the geographic concentration of publications does not straightforwardly imply a parochialism of perspective, though it does raise questions about whose research agenda dominates the framing of engagement and disengagement in AI-enabled education.

3.4 Thematic map

Figure 8 (Thematic Map) reveals four distinct quadrants. The motor themes quadrant (top-right) is dominated by ChatGPT, generative AI, and large language models highly developed

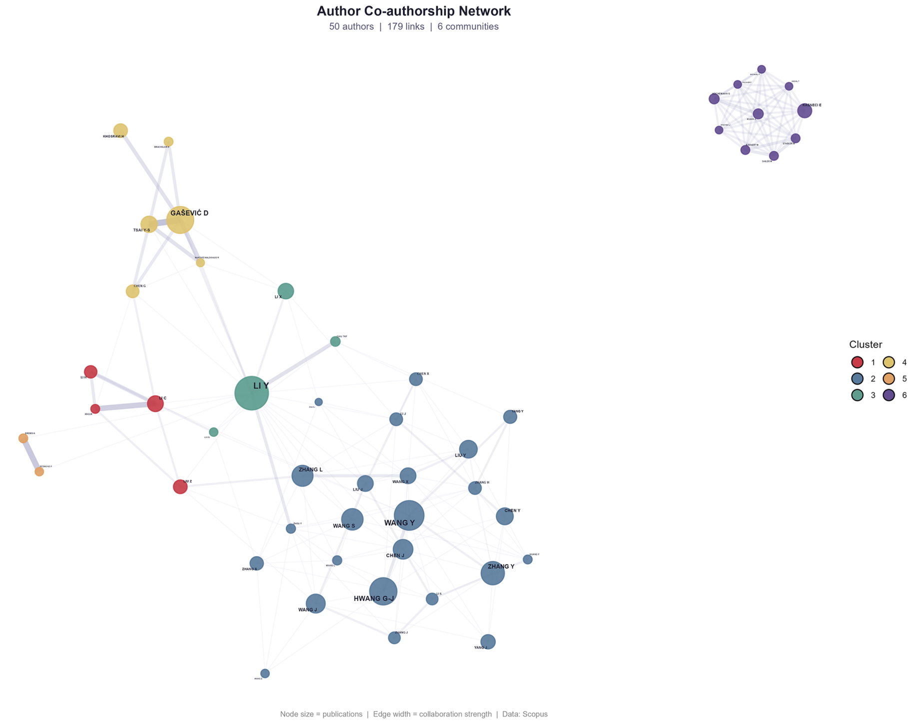

Figure 5. Co-authorship network. Source: Scopus data base

and central topics driving current research. The niche themes (top-left) include learning analytics, student engagement, deep learning, and machine learn well-developed but relatively specialised. The basic themes (bottom-right) artificial intelligence, higher education, educational technology represent foundational and widely connected topics. The emerging or declining themes (bottom-left) gamification, adaptive learning, intelligent tutoring systems, and virtual/augmented reality indicate areas in early stages or losing prominence.

The positioning of ‘student engagement’ in the Niche Themes quadrant high density but lower centrality is analytically significant. It indicates that engagement research is internally coherent and well-developed but has not yet fully diffused its insights into the broader field. Cognitive disengagement is notably absent from the motor or basic themes quadrants entirely, confirming its status as an underexplored construct in terms of structural positioning within the field’s knowledge architecture, regardless of its frequency in adjacent literature.

3.5 Top institutions

Table 7 confirms the dominance of Hong Kong and Chinese mainland institutions, with The Chinese University of Hong Kong (54 publications) and The University of Hong Kong (53) leading. Monash University (Australia) and Nanyang Technological University (Singapore) represent the broader Asia-Pacific contribution. Western institutions such as the University of Florida (32) and University of Michigan (25) are present but comparatively less dominant.

3.6 Top cited papers and Braford/Lotka analysis

Table 8 reveals that Kasneci *et al.* (2023) with 3,955 citations is the most influential work, reflecting the central role of ChatGPT in reshaping scholarly discourse. Highly cited studies

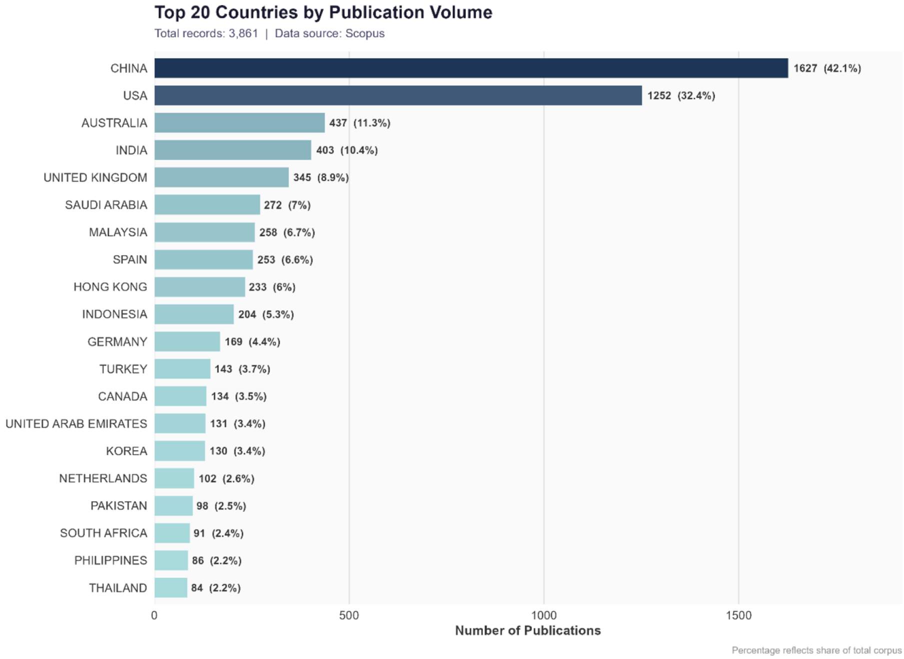

Figure 6. Countries by publication volume. Source: Scopus data base

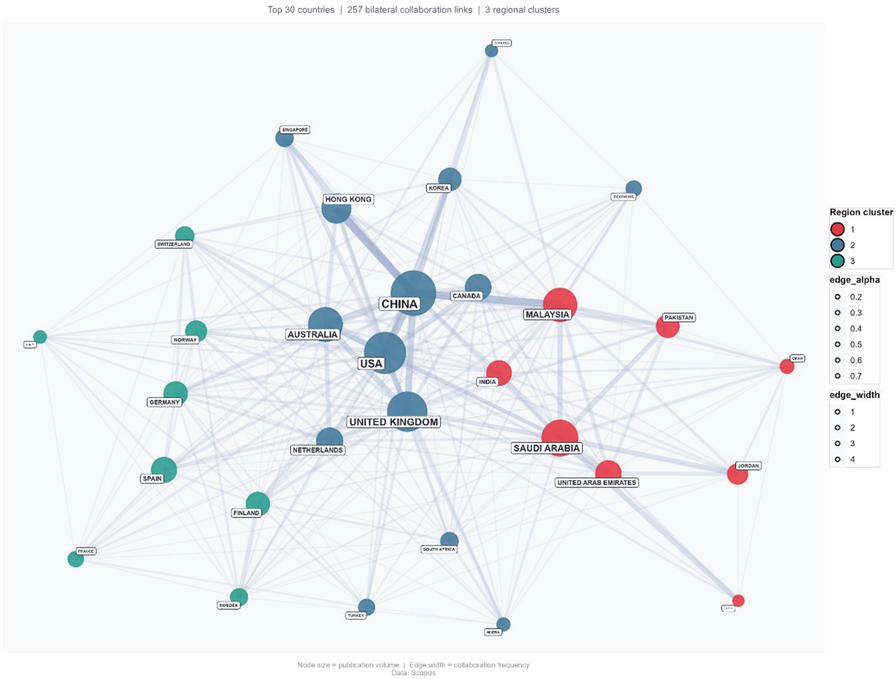

Figure 7. Country collaboration network. Source: Scopus data base

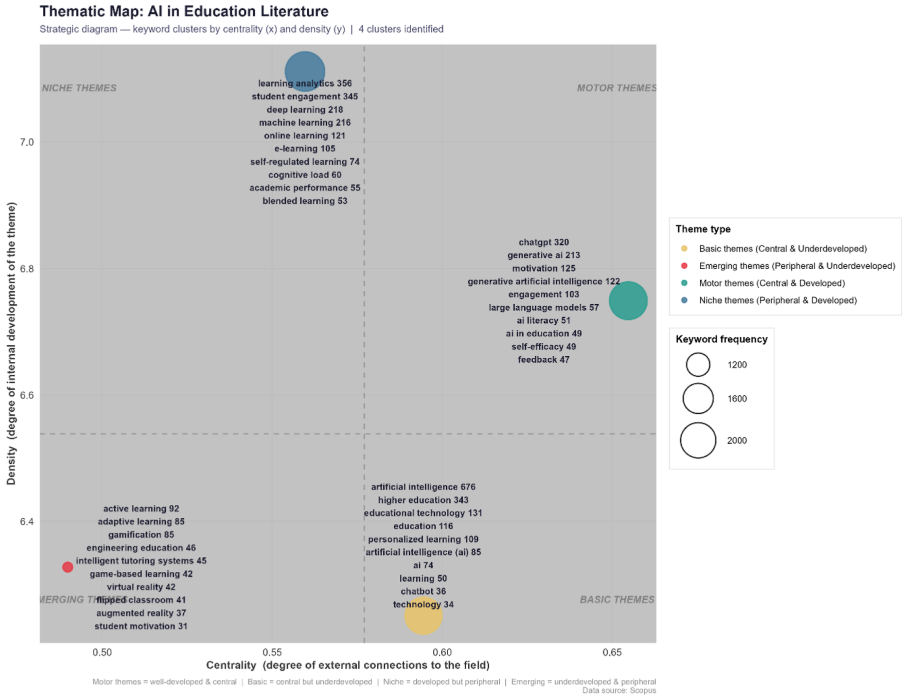

Figure 8. Thematic map. Source: Scopus data base

Table 7. Top institutions

Institution	Publications
THE CHINESE UNIVERSITY OF HONG KONG	54
THE UNIVERSITY OF HONG KONG	53
ZHEJIANG UNIVERSITY	50
THE EDUCATION UNIVERSITY OF HONG KONG	49
MONASH UNIVERSITY	48
NANYANG TECHNOLOGICAL UNIVERSITY	48
CENTRAL CHINA NORMAL UNIVERSITY	47
NATIONAL TAIWAN UNIVERSITY OF SCIENCE AND TECHNOLOGY	38
UNIVERSITY OF FLORIDA	32
UNIVERSITY OF SOUTHERN QUEENSLAND	31
ZHEJIANG NORMAL UNIVERSITY	29
BEIJING NORMAL UNIVERSITY	28
KING ABDULAZIZ UNIVERSITY	28
NATIONAL TAICHUNG UNIVERSITY OF EDUCATION	27
KING FAISAL UNIVERSITY	26
THE HONG KONG POLYTECHNIC UNIVERSITY	26
UNIVERSITI SAINS MALAYSIA	25
UNIVERSITY OF MICHIGAN	25
EAST CHINA NORMAL UNIVERSITY	23
SOUTH CHINA NORMAL UNIVERSITY	23

Source(s): Scopus data base

emphasise academic integrity, adaptive learning, AI literacy, and personalised learning. Earlier influential works (2016–2020) focus on engagement, MOOCs, and learning analytics, forming the foundational base, while recent high-citation papers (2022–2024) concentrate on generative AI and AI-driven learning systems.

3.6.1 Evaluation under Braford's law and Lotka's author productivity concept. The Bradford's Law distribution (Figure 9) clearly shows a core set of journals contributing a disproportionately high number of publications in AI-in-education research. A small group of leading sources, including *Education and Information Technologies*, *IEEE Access*, and *Education Sciences*, form the core zone, where publication frequency is highest. Beyond this core, the number of articles declines sharply across successive zones, indicating a typical Bradford scattering pattern. This suggests that while a few journals dominate knowledge production, a large number of peripheral journals contribute relatively fewer articles. The pattern confirms a high concentration of research output within a limited set of influential journals, supporting the existence of well-established publication hubs in the field.

The results strongly support Lotka's law (Table 9, Figure 10), showing a highly skewed distribution of author productivity in AI-in-education research. A large majority of authors (87.11%) have contributed only one publication, which is significantly higher than the theoretical expectation (61.77%), indicating a strong presence of occasional contributors. As the number of publications increases, the proportion of authors declines sharply, with very few authors producing more than five papers. This pattern reflects a highly dispersed authorship structure, where a small group of highly productive researchers coexists with a large base of one-time contributors. The deviation between observed and theoretical proportions suggests an even greater concentration of productivity at the lower end, reinforcing the competitive and expanding nature of the field.

3.7 Keyword evolution analysis

Figure 11 highlights the most frequently used author keywords. Artificial intelligence dominates by a substantial margin, confirming its central role across the corpus. ChatGPT, generative AI, and large language models appear as prominent recent keywords, reflecting the post-2022 surge in generative AI research. It is important to note, however, that the high frequency of 'artificial intelligence' as a keyword cannot be interpreted as evidence of generative AI prevalence specifically these terms represent distinct concepts. The temporal evolution of keyword frequencies (Figure 14) must be consulted to draw conclusions about the timing and direction of the generative AI surge.

The treemap (Figure 12) presents the relative prominence of key research themes based on keyword frequency, highlighting the dominant areas in AI-in-education literature. Artificial intelligence occupies the largest area, confirming its central position. Student engagement, higher education, and learning analytics represent the next tier of prominent terms, indicating strong emphasis on learner-focused and data-driven educational approaches. ChatGPT and generative AI appear as sizeable segments, reflecting recent growth in these specific areas. Importantly, the co-presence of keywords such as cognitive load, academic integrity, and critical thinking though smaller in area suggests growing concern for cognitive and ethical dimensions of AI use in education.

Figure 13 (Keyword Frequency Evolution Heatmap, 2017–2026) illustrates the temporal growth of key research themes. Early years (2017–2020) show relatively stable and low activity, reflecting a developmental phase. From 2021 onwards a gradual increase is observed, with a sharp surge after 2023, particularly for artificial intelligence, student engagement, and higher education. Notably, ChatGPT and generative AI emerge prominently from 2023, reaching peak frequencies in 2024–2025.

The heatmap provides the longitudinal evidence that the treemap (Figure 13) cannot. The temporal concentration of generative AI keyword frequency in 2023–2025 confirms that the field's shift toward learner-centered and generative AI-driven themes is a recent and rapid

Table 8. Top cited papers

Authors	Title	Journal	Citations
Kasneci *et al.* (2023)	Chatgpt for good? On opportunities and challenges of large language models for education	Learning And Individual Differences	3,955
Cotton *et al.* (2024)	Chatting and cheating: ensuring academic integrity in the era of chatgpt	Innovations In Education And Teaching International	1,578
Gligorea *et al.* (2023)	Adaptive learning using artificial intelligence in e-learning: a literature review	Education Sciences	627
Southworth *et al.* (2023)	Developing a model for ai across the curriculum: transforming the higher education landscape via innovation in ai literacy	Computers And Education: Artificial Intelligence	462
Huang *et al.* (2023)	Effects of artificial intelligenceâ "enabled personalized recommendations on learnersâ learning engagement, motivation, and outcomes in a flipped classroom	Computers And Education	448
Chiu *et al.* (2024)	Teacher support and student motivation to learn with artificial intelligence (ai) based chatbot	Interactive Learning Environments	429
Song and Song (2023)	Enhancing academic writing skills and motivation: assessing the efficacy of chatgpt in ai-assisted language learning for EFL students	Frontiers In Psychology	429
Lin *et al.* (2023)	Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review	Smart Learning Environments	414
Hew (2016)	Promoting engagement in online courses: what strategies can we learn from three highly rated moocs	British Journal Of Educational Technology	393
Xia *et al.* (2022)	A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education	Computers And Education	358
Tomasevic *et al.* (2020)	an overview and comparison of supervised data mining techniques for student exam performance prediction	Computers And Education	337
Dolmans *et al.* (2016)	Deep and surface learning in problem-based learning: a review of the literature	Advances In Health Sciences Education	335
De barba *et al.* (2016)	The role of students' motivation and participation in predicting performance in a MOOC	Journal Of Computer Assisted Learning	330
Timms (2016)	Letting artificial intelligence in education out of the box: educational cobots and smart classrooms	International journal of artificial intelligence in education	324
Hussain *et al.* (2018)	Student engagement predictions in an e-learning system and their impact on student course assessment scores	Computational intelligence and neuroscience	309
Essel *et al.* (2022)	The impact of a virtual teaching assistant (chatbot) on students' learning in ghanaian higher education	International journal of educational technology in higher education	304
Sajja *et al.* (2024)	Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education	Information (Switzerland)	289
Foroughi *et al.* (2024)	Determinants of intention to use chatgpt for educational purposes: findings from PLS-SEM and FSQCA	International journal of human-computer interaction	284

(*continued*)

Table 8. Continued

Authors	Title	Journal	Citations
Rajabalee and santally (2021)	Learner satisfaction, engagement and performances in an online module: implications for institutional e-learning policy	Education and information technologies	275
Ouyang *et al*. (2023)	Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course	International journal of educational technology in higher education	273

Source(s): Scopus data base

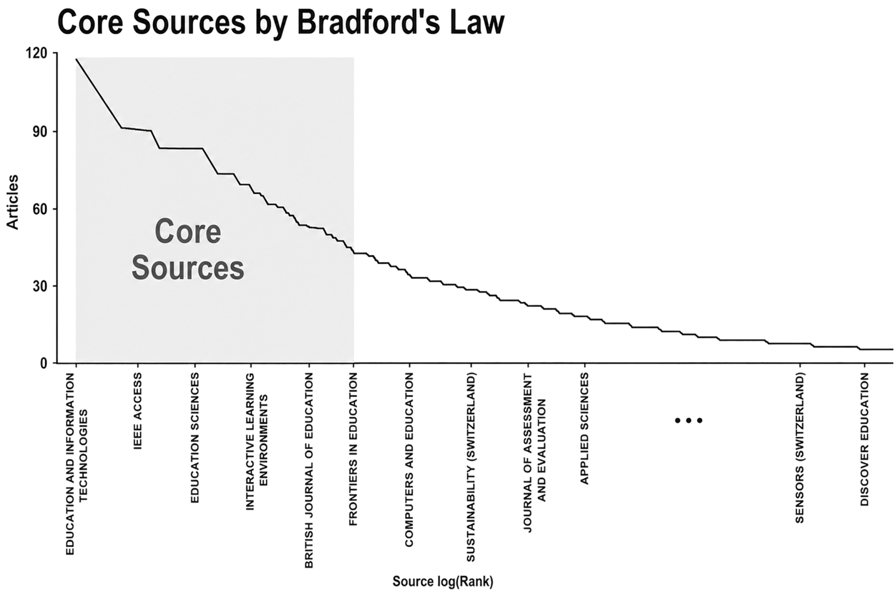

Figure 9. Bradford's law distribution. Source: Scopus data base

development rather than a gradual evolution, with direct implications for the maturity and consolidation of disengagement-focused research in this newer phase.

The bump chart (Figure 14) shows that learning analytics, student engagement, and machine learning occupied top positions in early years (2017–2021). From 2022 onwards, artificial intelligence rapidly rose to the top rank, maintaining dominance through 2026. ChatGPT and generative AI emerged sharply after 2023. Higher education and student engagement remain consistently within the top ranks, confirming their sustained importance as core application domains across all phases of the field's development.

3.8 Cognitive disengagement analysis

The thematic map (Figure 15) provides a strategic overview of the intellectual structure of AI-in-education research based on centrality and density. The motor themes quadrant (top-right) is dominated by ChatGPT, generative AI, and large language models, indicating that these topics are both highly developed and central to the field, driving current research directions. The

Table 9. LOTKA author productivity frequency table

Papers	Theoretical_ Prop	Theoretical_ Count	Authors	Observed_ Prop
1	0.61768	6330.6	8,928	0.871109
2	0.15442	1582.7	771	0.075227
3	0.068631	703.4	256	0.024978
4	0.038605	395.7	104	0.010147
5	0.024707	253.2	51	0.004976
6	0.017158	175.9	27	0.002634
7	0.012606	129.2	27	0.002634
8	0.009651	98.9	19	0.001854
9	0.007626	78.2	13	0.001268
10	0.006177	63.3	7	0.000683
11	0.005105	52.3	9	0.000878
12	0.004289	44	8	0.000781
13	0.003655	37.5	3	0.000293
14	0.003151	32.3	5	0.000488
15	0.002745	28.1	4	0.00039
16	0.002413	24.7	6	0.000585
17	0.002137	21.9	4	0.00039
18	0.001906	19.5	0	0
19	0.001711	17.5	1	9.76E-05
20	0.001544	15.8	0	0
21	0.001401	14.4	0	0
22	0.001276	13.1	0	0
23	0.001168	12	3	0.000293
24	0.001072	11	0	0
25	0.000988	10.1	0	0
26	0.000914	9.4	0	0
27	0.000847	8.7	0	0
28	0.000788	8.1	1	9.76E-05
29	0.000734	7.5	0	0
30	0.000686	7	0	0
31	0.000643	6.6	0	0
32	0.000603	6.2	0	0
33	0.000567	5.8	1	9.76E-05
34	0.000534	5.5	0	0
35	0.000504	5.2	0	0
36	0.000477	4.9	0	0
37	0.000451	4.6	0	0
38	0.000428	4.4	1	9.76E-05

Source(s): Scopus data base

niche themes (top-left) include learning analytics, student engagement, deep learning, and machine learning, which are well-developed but relatively specialized, with strong internal cohesion yet limited broader connectivity. The basic themes (bottom-right), such as artificial intelligence, higher education, and educational technology, represent foundational and widely connected topics that underpin the field but are less internally developed. The emerging or declining themes (bottom-left), including gamification, adaptive learning, intelligent tutoring systems, and virtual/augmented reality, indicate areas that are either in early stages of development or gradually losing prominence. Thus, the map reflects a clear transition toward generative AI-driven and learner-centric research, with engagement and AI applications becoming central to the evolving knowledge structure.

Figure 16 presents the distribution of disengagement-related constructs across the 2,692-paper disengagement sub-corpus. Student engagement dominates at 48.5%, followed by

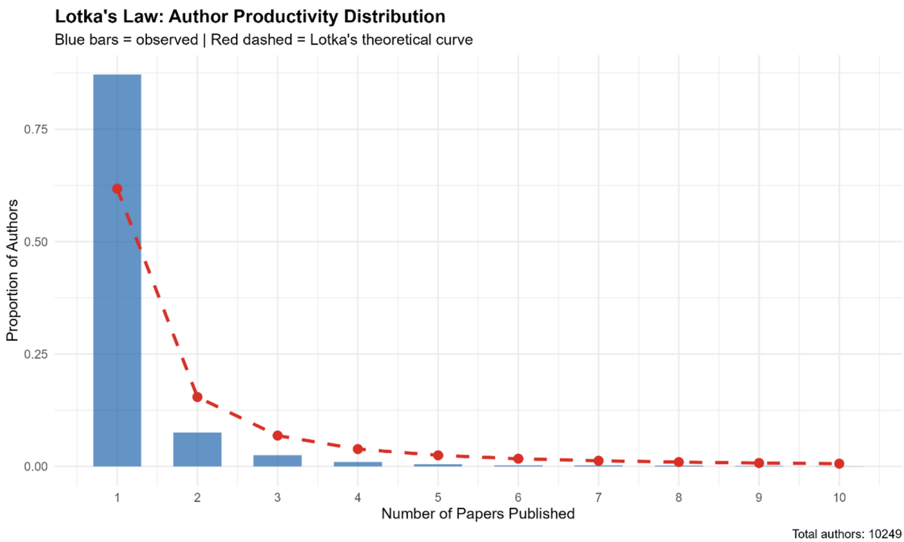

Figure 10. Lotka's law distribution. Source: Scopus data base

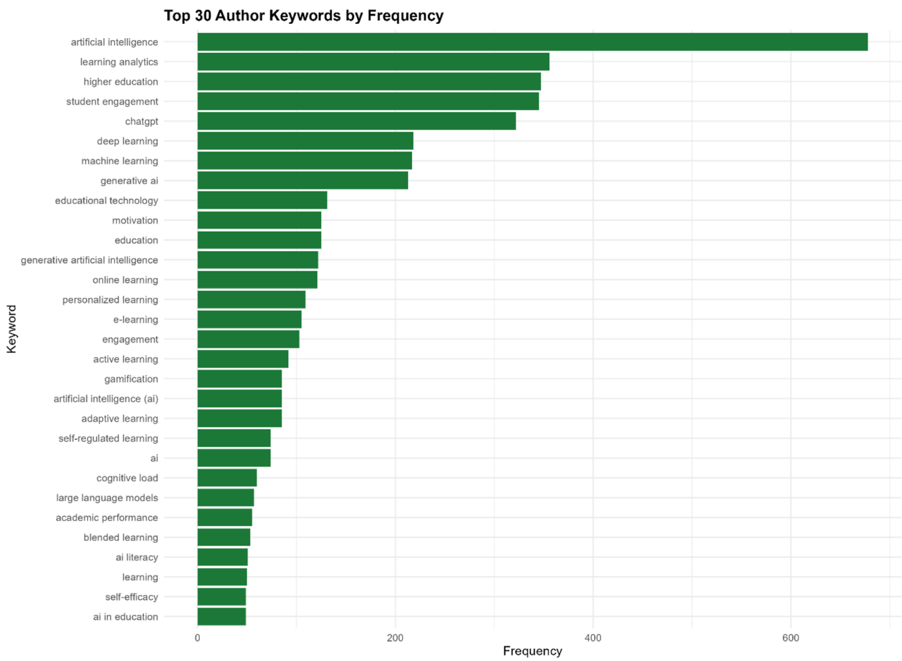

Figure 11. Keyword evolution frequency. Source: Scopus data base

motivation (29.1%) and attention (13.4%). Cognitive load accounts for 5.8% and explicit disengagement for only 2.2%. Boredom, low engagement, and learning fatigue are marginal.

This distribution requires careful interpretation in light of the clarification established in the Introduction and Abstract. The 2,692 papers in the disengagement sub-corpus all touch on

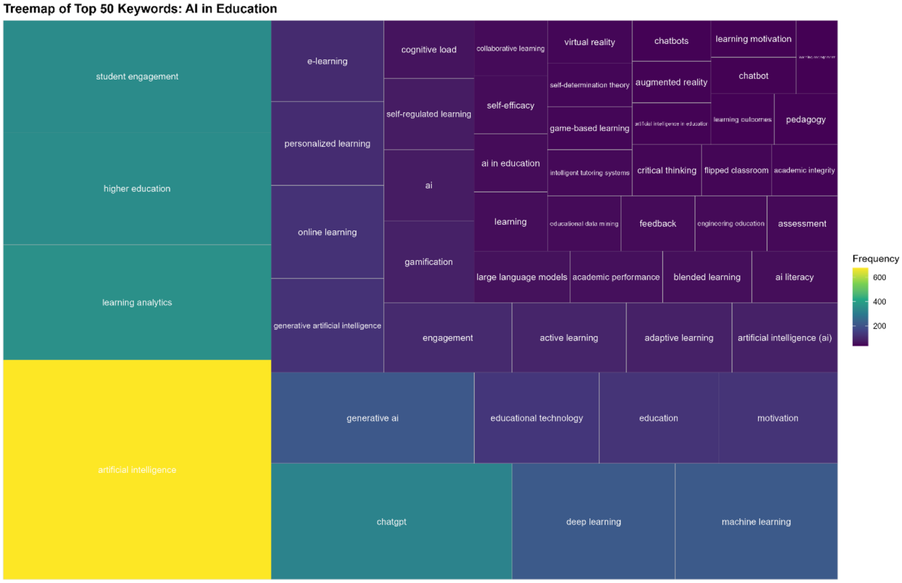

Figure 12. Tree map of top 50 key words. Source: Scopus data base

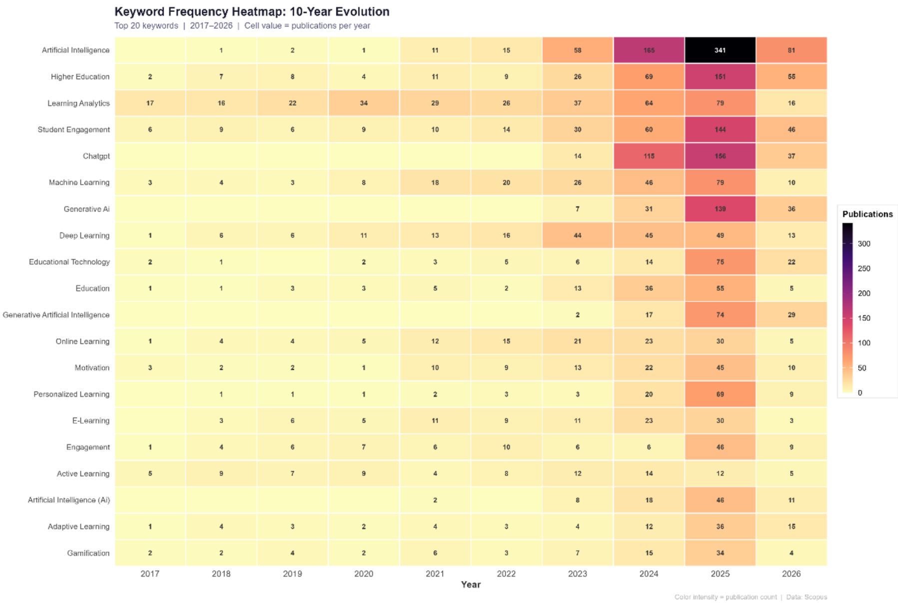

Figure 13. Keyword evolution map. Source: Scopus data base

constructs that are adjacent to or correlated with disengagement; however, the internal breakdown of Figure 16 reveals that the vast majority approach disengagement indirectly through positive constructs (engagement: 48.5%; motivation: 29.1%) rather than by directly

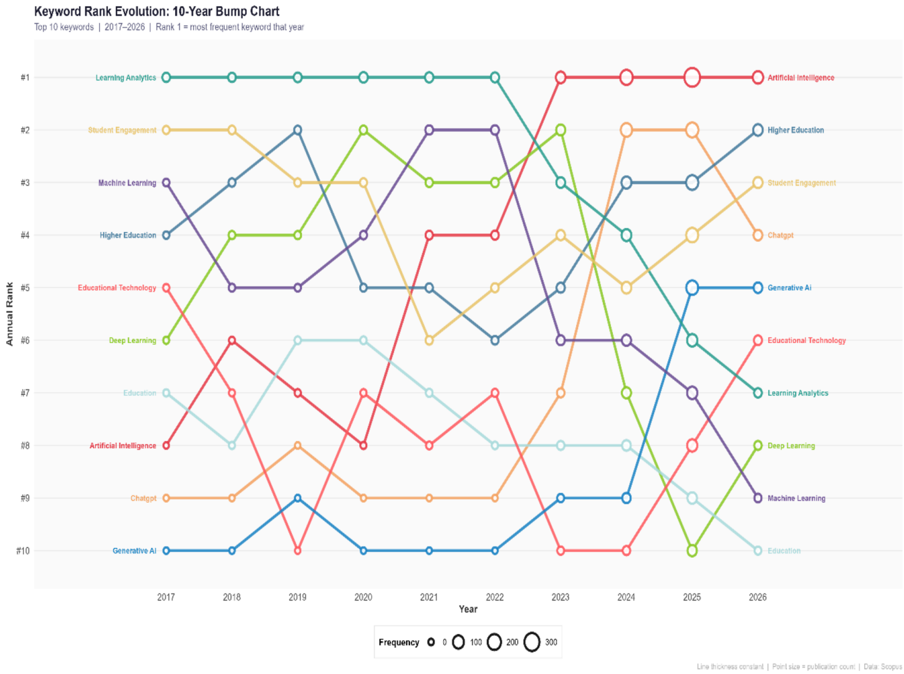

Figure 14. Keyword evolution bump chart. Source: Scopus data base

investigating disengagement, boredom, cognitive fatigue, or attentional decline as primary dependent variables. The 2.2% explicit disengagement figure is therefore the more important indicator of the construct's direct investigation status. This is not a contradiction of the 61–73% annual corpus proportion (Table 10) it is a clarification; many papers touch on disengagement territory without making it their primary focus.

The Figure 17 presents the most frequent keywords within the disengagement-related sub-corpus, highlighting the dominant themes associated with learner disengagement in AI-in-education research. Artificial intelligence leads by a substantial margin, followed by student engagement, higher education, and learning analytics, indicating that disengagement is primarily studied within broader AI-driven and higher education contexts. The strong presence of ChatGPT, generative AI, machine learning, and deep learning reflects the growing influence of advanced AI technologies in shaping disengagement-related discussions. At the same time, keywords such as motivation, cognitive load, self-regulated learning, and academic performance emphasize the psychological and behavioral dimensions linked to disengagement. Notably, direct disengagement terms remain less prominent compared to engagement-oriented constructs, suggesting that the literature largely approaches disengagement indirectly. Thus, the distribution reinforces the idea that disengagement is embedded within technology-driven, learner-centered, and performance-related research themes, rather than being treated as an independent research domain.

The co-occurrence network of the disengagement sub-corpus Figure 18 reveals a densely interconnected structure centered around core educational and AI-related concepts. Students, learning systems, teaching, and artificial intelligence emerge as central nodes, indicating that disengagement is primarily examined within the broader context of instructional systems and learner interaction. The network is divided into multiple clusters, reflecting distinct thematic groups, including technology-driven learning (e.g. e-learning, computer-aided instruction), learner-centered constructs (e.g. student engagement, motivation), and advanced AI

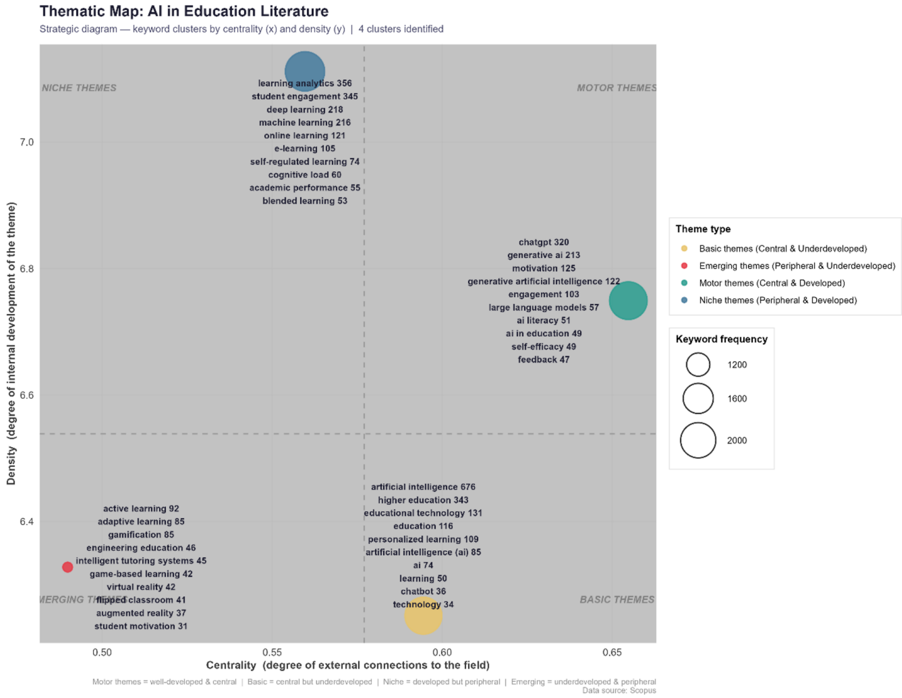

Figure 15. Cognitive disengagement aspects. Source: Scopus data base

techniques (e.g. deep learning, federated learning, adversarial machine learning). Strong linkages between student engagement, motivation, and learning highlight the close conceptual relationship between engagement and disengagement dimensions. Additionally, the presence of nodes related to human factors and behavioral aspects suggests an increasing integration of psychological perspectives in AI-driven education research. Finally, the network indicates that disengagement is not studied in isolation but is embedded within a complex, multidisciplinary framework combining AI technologies, pedagogy, and learner behavior.

The thematic map of the disengagement sub-corpus (Figure 19) reveals a structured distribution of research themes based on their centrality and development. The motor themes quadrant (top-right) is dominated by artificial intelligence, higher education, and ChatGPT, indicating that these are well-developed and highly central topics driving disengagement-related research. The basic themes (bottom-right) include student engagement, learning analytics, and deep learning, which are highly relevant to the field but comparatively less developed internally, suggesting their foundational role. The niche theme (top-left) represented by cognitive engagement is well-developed but relatively isolated, indicating limited integration with broader research streams. The emerging or declining themes (bottom-left), such as learning motivation and learning engagement, suggest areas that are either underdeveloped or losing prominence in the disengagement discourse. Additionally, themes like educational technology, personalized learning, and AI occupy an intermediate position, reflecting moderate development and connectivity. Overall, the map indicates that disengagement research is increasingly driven by AI and generative technologies, while core learner-centered constructs remain essential but require deeper conceptual integration.

Table 10 shows that cognitive disengagement-related studies consistently constitute 61–73% of AI-in-education research across 2015–2026. However, as established above, this

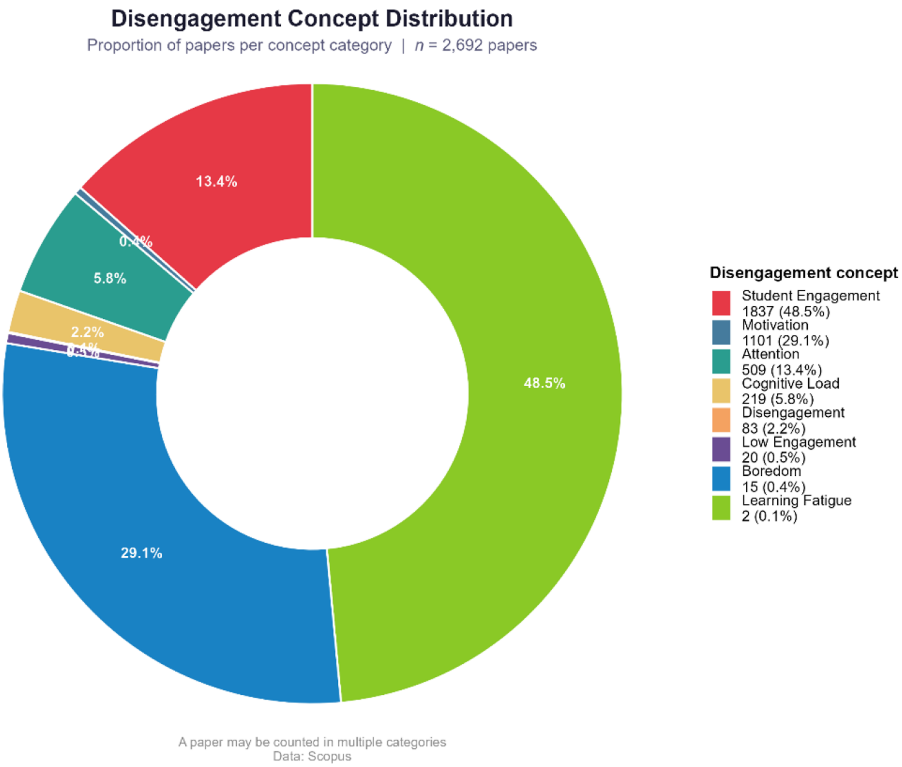

Figure 16. Distribution of disengagement-related constructs. Source: Scopus data base

Table 10. Cognitive disengagement annual trend

Year	Total_Papers	Disengagement_Papers	Percentage
2015	41	26	63.4
2016	53	38	71.7
2017	54	39	72.2
2018	82	54	65.9
2019	95	63	66.3
2020	103	63	61.2
2021	157	110	70.1
2022	187	130	69.5
2023	320	227	70.9
2024	749	508	67.8
2025	1,600	1,127	70.4
2026	420	307	73.1

Source(s): Scopus data base

high proportion reflects the prevalence of engagement-adjacent literature rather than explicit disengagement research. The slight dip in 2020 (61.2%) may reflect a temporary shift toward foundational technological exploration. The stable proportion across the sharp post-2023 growth period indicates that disengagement-adjacent themes scale proportionally with the

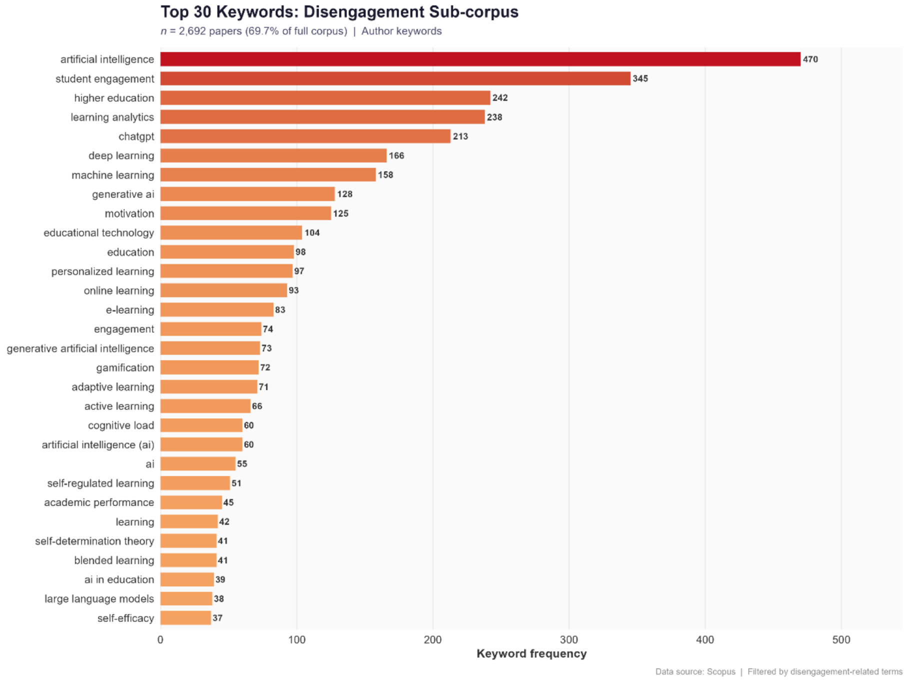

Figure 17. Frequent keywords within the disengagement-related sub-corpus. Source: Scopus data base

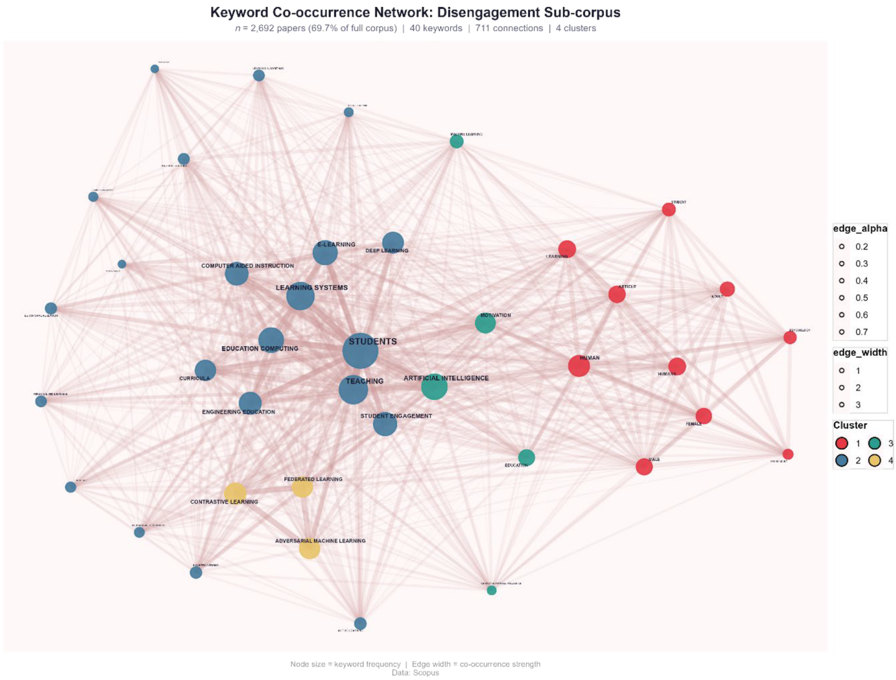

Figure 18. The co-occurrence network of the disengagement sub-corpus. Source: Scopus data base

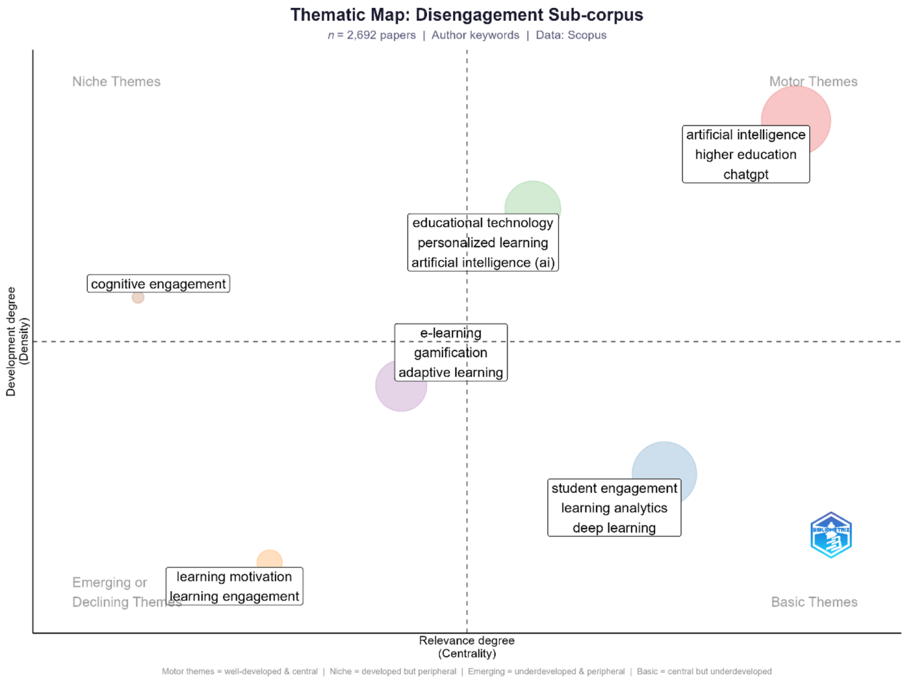

Figure 19. The thematic map of the disengagement sub-corpus. Source: Scopus data base

field's expansion, suggesting this is an enduring structural characteristic rather than a temporary pattern.

4. Discussion

The present bibliometric analysis offers a comprehensive understanding of the evolution, structure, and emerging directions of artificial intelligence (AI) in education, with a particular emphasis on student engagement and cognitive disengagement. The findings, taken together, suggest that the field is navigating a fundamental parado. AI technologies designed to enhance learning may simultaneously undermine the depth of cognitive engagement they are intended to support.

The observed transition from a technology-centric phase (2015–2020) to a learner-centered and generative AI-driven phase (post-2023), as evidenced by the publication trend (Table 1), keyword cluster shifts (Figure 14), and keyword rank evolution (Figure 16), is consistent with Engagement Theory, which emphasises meaningful interaction, collaboration, and active participation as core drivers of learning (Kearsley and Shneiderman, 1998). Earlier research focused on machine learning, learning analytics, and intelligent systems reflecting efficiency and prediction-oriented priorities aligned with system-focused perspectives. The rise of ChatGPT and generative AI from 2023 (Figure 14; Table 1) signals a move toward interactive and participatory environments where learners co-create knowledge rather than passively consume it. Yet, as the disengagement analysis (Figure 16; Table 10) reveals, this technological shift has not been accompanied by a proportional increase in research on what happens to cognitive engagement when AI takes on the generative role.

The central role of student engagement as the most critical bridging construct (betweenness centrality = 210.39, Table 3) can be interpreted through Self-Determination Theory (Reeve, 2012). SDT posits that learning is driven by autonomy, competence, and relatedness. Generative AI tools, particularly ChatGPT (betweenness = 114.8, Table 3), enhance perceived autonomy by enabling self-paced and personalised learning. However, the bibliometric evidence indicates a critical tension, while AI may increase surface autonomy, it may simultaneously reduce intrinsic cognitive effort and motivation when overused. This dual effect documented in the automation bias and over-reliance literature (Parasuraman and Riley, 1997; Kasneci *et al*., 2023) reflects a shift from active engagement to assisted engagement, where learners rely on AI-generated outputs rather than engaging deeply with learning material.

This tension is further explained through Cognitive Load Theory (Kirschner, 2002). AI tools can reduce extraneous cognitive load by simplifying complex tasks and providing instant feedback. However, the bibliometric evidence (Figure 16) indicates that this reduction may inadvertently lower germane cognitive load, which is essential for deep learning and knowledge construction. Notably, ‘cognitive load’ as a keyword appears in only 5.8% of the disengagement sub-corpus (Figure 16) despite its centrality in learning theory, confirming that the literature has not sufficiently addressed this critical trade-off. Consequently, while AI enhances efficiency, it may simultaneously contribute to cognitive disengagement characterised by reduced mental effort, shallow processing, and passive learning behaviours.

The disengagement-focused findings provide one of the most significant theoretical contributions of this study. As established in Section 3.9 and Figure 16, the literature remains heavily skewed toward positive constructs (engagement-48.5%; motivation-29.1%), treating disengagement primarily as the absence of engagement rather than as a distinct psychological and behavioral phenomenon. This reflects a limitation in current models, which tend to emphasise positive constructs while neglecting negative or counterproductive learning states. The findings therefore call for a dual-continuum framework, where engagement and disengagement are treated as interrelated but independent dimensions of learning in AI environments.

The emergence of generative AI as a motor theme (Figure 9) further deepens this theoretical discussion. Unlike earlier AI systems that supported instruction, generative AI actively produces content, answers, and solutions, shifting the locus of cognitive activity from the learner to the system. This raises concerns about epistemic dependency and reduced critical thinking a concern reinforced by the relatively low keyword prominence of “critical thinking” (239 occurrences, Table 3) compared to the dominance of “student engagement” (2,026 occurrences) and “artificial intelligence” (3,797 occurrences). From a constructivist perspective, this may weaken the learner’s role in knowledge construction, leading to a form of cognitive outsourcing where learning becomes externally mediated rather than internally processed.

The geographical and institutional concentration of research in Asia and the Asia-Pacific region (Figure 7; Table 7) adds another theoretical dimension. While the region demonstrates strong research productivity with China accounting for 42.1% of publications the findings suggest a dominance of technology-driven and output-oriented approaches. As noted in the literature on Confucian educational philosophy and state-directed AI policy in China, high-performance and examination-oriented educational cultures may produce research questions differently framed than those emerging from Western learner-centered traditions. This highlights the need for context-sensitive theoretical models that account for educational system diversity, cultural norms, and technological access patterns across regions.

Finally, the application of bibliometric laws (Bradford’s law, Figure 10; Lotka’s law, Figures 11 and 12) confirms the structural maturity of the field, characterised by concentrated publication outlets and a highly skewed authorship distribution. This suggests that AI-in-education research is evolving into a specialised and competitive domain where knowledge production is increasingly centralised yet rapidly expanding.

Thus, the findings extend existing theoretical perspectives by highlighting the need to move beyond a purely engagement-focused view of AI in education toward a more balanced framework that incorporates cognitive disengagement, attention dynamics, and depth of learning. The study introduces the notion of an AI-driven engagement-disengagement paradox, increased accessibility and efficiency may coexist with reduced cognitive effort and deeper learning. Addressing this paradox is essential for developing more effective, responsible, and learner-centered AI-enabled educational systems.

5. Implications

5.1 Theoretical implications

The findings call for a reframing of AI-in-education research by incorporating cognitive disengagement as a central construct rather than a peripheral outcome. The fact that explicit disengagement appears in only 2.2% of the disengagement sub-corpus (Figure 16), while engagement-adjacent constructs dominate, indicates that existing theoretical models are not adequately capturing the full cognitive spectrum of AI-mediated learning. Future studies should develop integrated theoretical models that connect AI usage with cognitive processes such as attention, motivation, self-regulation, and learning depth. The dual-continuum framework proposed here treating engagement and disengagement as independent but interrelated dimensions offers a concrete starting point for this theoretical development.

5.2 Practical implications for educators

For educators, the findings highlight the need to move beyond mere adoption of AI tools toward pedagogically informed integration. The low keyword prominence of “critical thinking” (239 occurrences; Table 3) relative to “student engagement” (2,026 occurrences) and “artificial intelligence” (3,797 occurrences) suggests that critical thinking is not being systematically cultivated alongside AI adoption in education. Practically, this means educators should: (1) design AI-assisted learning activities that require students to evaluate, question, or extend AI-generated outputs rather than simply accept them; (2) develop AI literacy curricula that explicitly address automation bias and over-reliance; and (3) build in metacognitive checkpoints where learners reflect on whether they are engaging deeply with content or delegating cognitive effort to the AI system. Given that cognitive load appears in only 5.8% of the disengagement sub-corpus (Figure 16), educators cannot assume that existing AI tools include cognitive engagement monitoring they must design it in explicitly.

5.3 Implications for policy makers

The geographic concentration of AI-in-education research in China (42.1%) and the USA (32.4%) together accounting for nearly three-quarters of all publications (Figure 7) raises important policy questions about whose educational context shapes the field’s agenda. Policymakers in other regions, particularly developing economies in Southeast Asia, Africa, and Latin America, should be cautious about adopting AI education frameworks developed primarily in high-resource, high-performance educational cultures without contextual adaptation. Investment in regionally specific AI-in-education research, particularly focused on disengagement, attention, and cognitive load in diverse learning contexts, is a policy priority highlighted by this study’s geographic analysis.

5.4 Implications for future research

The findings outline several concrete directions for future research. First, direct empirical investigation of cognitive disengagement, boredom, and learning fatigue in AI-enabled learning environments constructs that collectively represent less than 3% of the current literature (Figure 16) is urgently needed. Second, longitudinal studies examining long-term AI impact on learning behaviour are required, as the current corpus is dominated by cross-sectional designs as evidenced by the citation patterns (Table 4) showing rapid publication growth without corresponding citation consolidation. Third, cross-cultural and multicontextual studies are needed to move beyond the Asia-Pacific and US research concentration (Figure 7). Fourth, mixed-method and experimental designs would complement the current bibliometric and correlational approaches. Fifth, a comparative analysis of the focused corpus used here (with engagement/disengagement search terms) against an unfiltered AI-in-education corpus would enable researchers to assess the representativeness of the current dataset and the true proportion of engagement-focused research within the broader field.

6. Conclusion

This study provides a comprehensive bibliometric examination of artificial intelligence (AI) in education, offering a structured understanding of its evolution, intellectual architecture, and emerging research priorities, with a particular emphasis on engagement and cognitive disengagement. The findings demonstrate that AI-in-education research has transitioned from an early exploratory phase centered on technological capabilities to a rapidly expanding, learner-centered paradigm, increasingly shaped by generative AI technologies such as ChatGPT and large language models.

The analysis identifies artificial intelligence, student engagement, higher education, and generative AI as the dominant and interconnected themes driving current research. While foundational areas such as learning analytics, machine learning, and educational technology continue to underpin the field, the growing prominence of generative AI (motor themes, Figure 9; keyword surge post-2023, Figure 14) reflects a significant shift toward interactive, adaptive, and content-generating systems that directly influence learning processes. Student engagement functions as the central bridging construct (betweenness centrality = 210.39, Table 3), linking technological advancements with pedagogical outcomes.

A central contribution of this study is the clarification and reconciliation of the disengagement paradox. While disengagement-adjacent constructs appear in 61–73% of the annual corpus (Table 10), explicit cognitive disengagement as an independently investigated construct accounts for only 2.2% of the disengagement sub-corpus (Figure 16). These findings are complementary rather than contradictory. They together reveal that the field is extensively aware of disengagement as a concern but has not yet committed to studying it directly. This imbalance constitutes a structural gap in the AI-in-education research architecture that future empirical work must address.

The study also reveals a geographically concentrated yet globally collaborative research landscape (Figures 7 and 8), with China and the Asia-Pacific region dominating publication output. This concentration raises questions about the generalisability of current findings across diverse educational systems and cultural contexts, and points to a need for broader regional representation in future research.

Finally, the study introduces the concept of the AI-driven engagement-disengagement paradox, technologies designed to enhance learning efficiency and personalisation may simultaneously create conditions for reduced cognitive effort, passive participation, and diminished critical thinking. Addressing this paradox through theoretically grounded, empirically rigorous, and culturally sensitive research is the defining challenge for the next phase of AI-in-education scholarship.

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