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# From Intelligent Tutoring Systems to Generative AI: Changing Educational Priorities in Research Involving Asian-Affiliated Scholars

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## ABSTRACT

*This study examines how educational priorities have changed in artificial intelligence (AI) research involving scholars affiliated with institutions in 34 Asian countries and territories. It analyses 1,585 English-language Scopus journal articles published between 2010 and 2026, with partial coverage for 2026 up to 23 May. Biblioshiny was used to map keyword co-occurrence, thematic positioning, and thematic evolution across three periods: 2010–2016, 2017–2020, and 2021–2026. TALL was applied to a random sample of 792 abstracts to elaborate on the educational meanings embedded in the bibliometric structures. The findings indicate a reorientation from computer-aided instruction, intelligent tutoring systems, and learning systems towards generative AI, ChatGPT, technology adoption, and emerging human–AI discourses. Higher education and students provide the field's principal educational focus, although students are frequently positioned as technology users or as adopters. Pedagogical mechanisms, teacher agency, assessment redesign, and responsible-use competencies remain less integrated. AI literacy, academic integrity, ethics, and critical thinking are visible but remain embedded within the broader technology and adoption structure. Abstract-level patterns further revealed benefit-oriented framing around support, enhancement, and future potential, which should not be interpreted as evidence of educational effectiveness. The study contributes an education-centred account of how technological expansion has outpaced the conceptual integration of pedagogy, human agency, assessment, and responsible institutional conditions.*

**Keywords:** *artificial intelligence in education, generative AI, education technology, bibliometric analysis, textual analysis, Asian-affiliated scholarship.*

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## INTRODUCTION

Artificial intelligence in education (AIEd) has moved through successive configurations, from computer-aided instruction, intelligent tutoring systems, adaptive learning, and automated feedback to accessible generative tools.[1] Large language models, such as ChatGPT, are now directly available to students and teachers, extending attention beyond specialised systems and raising questions about adoption,[2] human–AI interaction,[3] academic integrity,[4] and institutional responses.[5] Nevertheless, technological prominence does not demonstrate pedagogical knowledge or educational effectiveness.[6]

Recent reviews indicate a substantial AIED literature in higher education, focusing more on students than on instructors.[7] They call for stronger conceptual grounding, ethical attention, interdisciplinary collaboration and methodological rigour.[8] Large language models may provide explanations, feedback, personalised support, and content generation, but also raise concerns about reliability, bias, dependence, and academic integrity.[9] Recent synthesis indicates that pedagogical implementation remains less developed than the discussion of technological possibilities and adoption.[10]

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[1] Melissa Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour," *International Journal of Educational Technology in Higher Education* 21, no. 1 (January 19, 2024): 4, https://doi.org/10.1186/s41239-023-00436-z; Shan Wang et al., "Artificial Intelligence in Education: A Systematic Literature Review," *Expert Systems with Applications* 252 (October 2024): 124167, https://doi.org/10.1016/j.eswa.2024.124167; Sirine Bouguettaya et al., "A Meta-Survey of Generative AI in Education: Trends, Challenges, and Research Directions," *Big Data and Cognitive Computing* 9, no. 9 (September 16, 2025): 237, https://doi.org/10.3390/bdcc9090237; Fan Ouyang and Pengcheng Jiao, "Artificial Intelligence in Education: The Three Paradigms," *Computers and Education: Artificial Intelligence* 2 (2021): 100020, https://doi.org/10.1016/j.caeai.2021.100020.

[2] Defne Yigci et al., "Large Language Model-Based Chatbots in Higher Education," *Advanced Intelligent Systems* 7, no. 3 (March 11, 2025), https://doi.org/10.1002/aisy.202400429.

[3] Sahil Sharma et al., "The Role of Large Language Models in Personalized Learning: A Systematic Review of Educational Impact," *Discover Sustainability* 6, no. 1 (April 4, 2025): 243, https://doi.org/10.1007/s43621-025-01094-z.

[4] Mike Perkins, "Academic Integrity Considerations of AI Large Language Models in the Post-Pandemic Era: ChatGPT and Beyond," *Journal of University Teaching and Learning Practice* 20, no. 2 (January 1, 2023), https://doi.org/10.53761/1.20.02.07.

[5] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Enkelejda Kasneci et al., "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education," *Learning and Individual Differences* 103 (April 2023): 102274, https://doi.org/10.1016/j.lindif.2023.102274.

[6] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Thomas K.F. Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education," *Computers and Education: Artificial Intelligence* 4 (2023): 100118, https://doi.org/10.1016/j.caeai.2022.100118.

[7] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Helen Crompton and Diane Burke, "Artificial Intelligence in Higher Education: The State of the Field," *International Journal of Educational Technology in Higher Education* 20, no. 1 (April 24, 2023): 22, https://doi.org/10.1186/s41239-023-00392-8.

[8] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour."

[9] Kasneci et al., "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education"; Lasha Labadze, Maya Grigolia, and Lela Machaidze, "Role of AI Chatbots in Education: Systematic Literature Review," *International Journal of Educational Technology in Higher Education* 20, no. 1 (October 31, 2023): 56, https://doi.org/10.1186/s41239-023-00426-1.

[10] Marina Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies," *Computers and Education: Artificial Intelligence* 8 (June 2025): 100407, https://doi.org/10.1016/j.caeai.2025.100407; Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education."

This imbalance creates educational problems. References to students, learning, teaching, or assessment did not specify how AI supports learning.[11] The inclusion of teachers in technology-use studies likewise does not establish their agency over instructional design or appropriate use decisions.[12] Assessment may be reduced to misconduct; however, AI also challenges what should be assessed, how learning should be evidenced, and which human or AI-assisted performances are educationally valid.[13] Responsible use exceeds the institutional compliance. AI literacy includes understanding, application, evaluation, creation, and ethical judgement,[14] whereas AIED ethics encompass pedagogy, teacher roles, assessment, human cognition, and educational power relations.[15]

Science mapping can locate and connect these issues. Keyword co-occurrence networks identify conceptual communities, thematic maps represent connectedness and coherence, and period-specific maps support temporal comparisons.[16] Nevertheless, keywords compress the the article's content. Abstract-level text analysis can elaborate on the actors, processes, and educational claims underlying bibliometric structures without independently validating them.[17]

Geographical framing requires precision and accuracy to avoid misinterpretation. Asia is not treated as educationally homogeneous, nor are all the studies included assumed to have been conducted in Asia. The corpus comprises works by authors affiliated with institutions in 34 Asian countries and territories, including international collaborations.[18] This

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[11] Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies"; Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education."

[12] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Ismail Celik et al., "The Promises and Challenges of Artificial Intelligence for Teachers: A Systematic Review of Research," *TechTrends* 66, no. 4 (July 25, 2022): 616–30, https://doi.org/10.1007/s11528-022-00715-y.

[13] Che Yee Lye and Lyndon Lim, "Generative Artificial Intelligence in Tertiary Education: Assessment Redesign Principles and Considerations," *Education Sciences* 14, no. 6 (May 26, 2024): 569, https://doi.org/10.3390/educsci14060569; Zachari Swiecki et al., "Assessment in the Age of Artificial Intelligence," *Computers and Education: Artificial Intelligence* 3 (2022): 100075, https://doi.org/10.1016/j.caeai.2022.100075.

[14] Thomas K.F. Chiu et al., "What Are Artificial Intelligence Literacy and Competency? A Comprehensive Framework to Support Them," *Computers and Education Open* 6 (June 2024): 100171, https://doi.org/10.1016/j.caeo.2024.100171; Davy Tsz Kit Ng et al., "Conceptualizing AI Literacy: An Exploratory Review," *Computers and Education: Artificial Intelligence* 2 (2021): 100041, https://doi.org/10.1016/j.caeai.2021.100041.

[15] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Wayne Holmes et al., "Ethics of AI in Education: Towards a Community-Wide Framework," *International Journal of Artificial Intelligence in Education* 32, no. 3 (September 2022): 504–26, https://doi.org/10.1007/s40593-021-00239-1.

[16] Haojing Chen, YP Tsang, and CH Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities," *International Journal of Engineering Business Management* 15 (February 18, 2023), https://doi.org/10.1177/18479790231222349; Anton Klarin, "How to Conduct a Bibliometric Content Analysis: Guidelines and Contributions of Content Co-occurrence or Co-word Literature Reviews," *International Journal of Consumer Studies* 48, no. 2 (March 8, 2024), https://doi.org/10.1111/ijcs.13031.

[17] Chen, Tsang, and Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities."

[18] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour."

affiliation-based definition captures transnational scholarship while keeping the author'sthor's location distinct from the study setting.[19]

Accordingly, this study examines 1,585 Scopus-indexed journal articles published between 2010 and 2026, with partial coverage for 2026 up to 23 May. Biblioshiny provides primary evidence through co-word mapping, thematic positioning, and thematic evolution, whereas TALL elaborates on these structures using a random sample of 792 abstracts. This study addresses the following four research questions (RQ):

RQ1. How is AI-in-education research involving Asian-affiliated scholars organised into conceptual communities, and what educational actors, processes, and concerns characterise these communities?

RQ2. How are the major conceptual communities positioned in terms of thematic centrality and density, and what does their positioning indicate about the integration of technological innovation with pedagogy, learner development and sustainable educational development?

RQ3. How have educational themes and their conceptual linkages evolved across the foundational (2010–2016), transitional (2017–2020), and recent acceleration periods (2021–2026)?

RQ4. How do abstract-level lexical and topic patterns elaborate on the educational meanings embedded in bibliometric structures, particularly those concerning learning, teaching, assessment, technology adoption, AI literacy, and responsible AI use?

By addressing these questions, the study contributes an education-centred account of the field's movement from system-oriented instructional technologies towards generative, adoption-oriented, and emerging human–AI discourses. It further identifies where technological development has advanced more rapidly than the conceptual integration of pedagogy, teacher agency, assessment redesign, and responsible use competencies.

## METHOD

This study used a two-layer design that combined bibliometric science mapping with a nested abstract-level textual analysis.[20] Bibliometric mapping supplied the primary evidence for conceptual structure, strategic positioning, and temporal development, and abstract analysis elaborated on the educational meanings expressed in the abstracts. The second layer was neither an independent corpus, comparative analysis, nor statistical validation of the bibliometric findings. The outputs were connected only during the interpretation.

Scopus records were retrieved on 23 May 2026; consequently, the 2026 coverage was partial. The query combined AI terms—including intelligent systems, machine learning, chatbots, large language models, and generative AI—with terms related to education,

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[19] Philip J. Purnell, "Geodiversity of Research: Geographical Topic Focus, Author Location, and Collaboration. A Case Study of SDG 2: Zero Hunger," *Scientometrics* 129, no. 5 (May 22, 2024): 2701–27, https://doi.org/10.1007/s11192-024-04994-5.

[20] Chen, Tsang, and Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities"; Klarin, "How to Conduct a Bibliometric Content Analysis: Guidelines and Contributions of Content Co-occurrence or Co-word Literature Reviews."

teaching, learning, students, and educational institutions. Eligibility was restricted to English-language journal articles indexed under Social Sciences or Psychology. Geographic eligibility used the affiliation-country field: a record qualified when at least one author held an institutional affiliation in one of the 34 Asian countries or territories. Consequently, the corpus represents scholarship involving Asian-affiliated authors, including international co-authorship, rather than only studies conducted in Asia.[21] The complete Scopus query and affiliation country lists are presented in Supplementary Tables S1 and S2.

The Scopus query was reproduced verbatim because its displayed syntax was generated automatically. Although the rendered string showed "PUBYEAR < 2025" after selecting 2026, the exported publication-year (PY) field contained 2025 and 2026 records. Temporal eligibility was therefore verified from the exported metadata rather than the display string. The corpus covered 2010–2026, with 2026 limited to records available for retrieval. It comprised 1,585 journal articles from 435 sources and 4,459 authors in total.

The corpus was analysed using Biblioshiny, a graphical interface for Bibliometrix.[22] Author keywords and Keywords Plus were combined as KW_Merged and then analysed as unigrams without stemming. The conceptual structure was examined through a co-occurrence network of the 50 leading merged keywords. Nodes denote keywords, links denote co-occurrence, and node size denotes frequency.[23] Communities were identified using Louvain modularity.[24] Betweenness, closeness, and PageRank were retained as relational metrics. Community names were assigned after inspection of the constituent terms and therefore represent interpretive summaries, not predetermined categories.

A thematic map was generated from the 250 most frequent merged keywords using a minimum frequency of seven, unigrams, no stemming, and Louvain clustering.[25] Themes were positioned by Callon centrality and density: centrality represented connections with the wider conceptual field, whereas density represented internal connections among constituent terms.[26] Neither indicator was interpreted as indicating research quality, educational effectiveness, or substantive maturity. The initial keyword communities were synthesised

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[21] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Purnell, "Geodiversity of Research: Geographical Topic Focus, Author Location, and Collaboration. A Case Study of SDG 2: Zero Hunger."

[22] Massimo Aria and Corrado Cuccurullo, "Bibliometrix : An R-Tool for Comprehensive Science Mapping Analysis," *Journal of Informetrics* 11, no. 4 (November 2017): 959–75, https://doi.org/10.1016/j.joi.2017.08.007; Massimo Aria et al., "TALL: Text Analysis for All–an Interactive R-Shiny Application for Exploring, Modeling, and Visualizing Textual Data," *SoftwareX* 34 (June 2026): 102590, https://doi.org/10.1016/j.softx.2026.102590.

[23] Chen, Tsang, and Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities"; Klarin, "How to Conduct a Bibliometric Content Analysis: Guidelines and Contributions of Content Co-occurrence or Co-word Literature Reviews."

[24] Vincent D Blondel et al., "Fast Unfolding of Communities in Large Networks," *Journal of Statistical Mechanics: Theory and Experiment* 2008, no. 10 (October 1, 2008): P10008, https://doi.org/10.1088/1742-5468/2008/10/P10008; Santo Fortunato and Mark E. J. Newman, "20 Years of Network Community Detection," *Nature Physics* 18, no. 8 (August 29, 2022): 848–50, https://doi.org/10.1038/s41567-022-01716-7.

[25] Aria et al., "TALL: Text Analysis for All–an Interactive R-Shiny Application for Exploring, Modeling, and Visualizing Textual Data."

[26] Mario Angelelli et al., "Conceptual Structure and Thematic Evolution in Partial Least Squares Structural Equation Modeling Research," *Quality & Quantity* 59, no. 3 (June 6, 2025): 2753–98, https://doi.org/10.1007/s11135-025-02071-4.

into three macro-themes for reporting without changing their nodes, links, or community assignments.

Temporal development was examined using Trend Topics and period-specific thematic maps. Each map used the 250 most frequent merged keywords with a minimum frequency of five keywords. Maps were generated for 2010–2016, 2017–2020, and 2021–2026. The boundaries reflected changes visible in Trend Topics and Overall Evolution rather than equal intervals; the periods were labelled foundational, transitional, and recent acceleration. Themes were positioned by centrality and density and interpreted as motor, basic, niche, or emerging or declining themes.[27] Comparisons describe changes in composition and strategic position, not direct thematic lineage or causal succession. Unequal publication volumes were retained as corpus features, and the final period included only records available until 23 May 2026.

For textual elaboration, TALL was applied to a random 50% of the available abstracts. Because the corpus contained an odd number of records, the sample comprised 792 abstracts (49.97% of the complete data set). Pre-processing used TALL's GUM-based tokenisation, lemmatisation, and part-of-speech pipeline.[28] The processed corpus comprised 172,970 tokens, 7,635 lemma, and 7,437 sentences. For corpus-level processing and annual summaries, abstracts were organised into 17 year-based units covering 2010–2026. Thus, "Documents = 17" in the TALL overview denotes annual aggregation units and not sampled abstracts.

The main textual analyses were limited to lemma frequencies and topic modelling because these outputs addressed the educational meanings of bibliometric structures. Candidate solutions were assessed using TALL's K-choice diagnostics and the semantic distinctiveness and interpretability of their term distributions, combining model-based criteria with substantive inspection.[29] Five topics were retained because they yielded distinguishable vocabularies concerning university student adoption, learning design and engagement, educational development and digital skills, teachers and responsible use, and ChatGPT-oriented opportunity framing. Interpretation relied on beta probabilities to discriminate terms rather than automatically generated labels. Sentiment, emotion, morphological, syntactic, and subject–verb–object outputs were excluded from the main claims because they did not directly address the research questions, and some were sensitive to the publisher boilerplate. Their diagnostic treatment is described in the Supplementary Materials.

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[27] Angelelli et al.; Massimo Aria et al., "Comparative Science Mapping: A Novel Conceptual Structure Analysis with Metadata," *Scientometrics* 129, no. 11 (November 28, 2024): 7055–81, https://doi.org/10.1007/s11192-024-05161-6.

[28] Aria et al., "TALL: Text Analysis for All–an Interactive R-Shiny Application for Exploring, Modeling, and Visualizing Textual Data."

[29] Amer Farea et al., "Investigating the Optimal Number of Topics by Advanced Text-Mining Techniques: Sustainable Energy Research," *Engineering Applications of Artificial Intelligence* 136 (October 2024): 108877, https://doi.org/10.1016/j.engappai.2024.108877; Petro Tolochko et al., "What's in a Name? The Effect of Named Entities on Topic Modelling Interpretability," *Communication Methods and Measures* 18, no. 4 (October 29, 2024): 349–70, https://doi.org/10.1080/19312458.2024.2302120.

Integration occurred sequentially during interpretation, consistent with the use of text mining to elaborate science-mapping outputs.[30] The Biblioshiny communities, thematic positions, and period-specific patterns were interpreted first. TALL frequencies and topics were then used to clarify how abstracts articulated educational actors, processes and concerns within those structures. Textual results qualify the bibliometric interpretation regarding adoption, pedagogy, teacher roles, assessment, AI literacy, ethics, and benefit-oriented language. They did not reassign keywords, reproduce bibliometric clusters, or treat textual correspondence as an independent validation.

## RESULTS AND DISCUSSION

### Results

The final corpus comprised 1,585 journal articles published across 435 sources from 2010 to 2026. The records involved 4,459 authors, and 33.25% of the articles included international coauthorship. Annual production remained below ten articles per year until 2017, before increasing to 22 articles in 2020, 64 in 2022, 137 in 2023, 283 in 2024, and 633 in 2025. A further 330 articles were indexed in 2026 by the retrieval date of 23 May. Therefore, the 2026 count represents partial-year coverage and should not be interpreted as a decline from 2025. Biblioshiny calculated an annual growth rate of 31.76%, whereas the mean document age of 1.88 years reflected the concentration of publications in the most recent period.

**Table 1**. Corpus profile and analytical coverage, adopted from Biblioshiny and TALL analysis.[31]

| Analytical layer | Indicator | Result | Qualification |
|---|---|---:|---|
| **Biblioshiny corpus** | Publication period | 2010–2026 | The 2026 coverage includes records indexed until 23 May 2026. |
| | Articles | 1,585 | All records were Scopus-indexed journal articles. |
| | Sources | 435 | Sources refer to journals that are represented in the final corpus. |
| | Authors | 4,459 | Authors were identified using bibliographic metadata. |
| | Annual growth rate | 31.76% | Calculated by Biblioshiny for the entire publication period. |
| | Co-authors per article | 3.56 | Indicates the average number of contributing authors per the record. |
| | International co-authorship | 33.25% | Refers to articles involving authors from more than one country. |
| **Geographical coverage** | Asian countries and territories represented | 34 | Coverage was determined from author affiliation data. |
| **Temporal distribution** | Foundational period, 2010–2016 | 39 articles (2.46%) | Period boundary derived from the trend topic and thematic evolution outputs. |

[30] Chen, Tsang, and Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities"; Michelangelo Misuraca, "Text Mining in Bibliometrics and Science Mapping: A Methodological Review," *WIREs Computational Statistics* 18, no. 2 (June 28, 2026), https://doi.org/10.1002/wics.70066.

[31] Aria et al., "TALL: Text Analysis for All–an Interactive R-Shiny Application for Exploring, Modeling, and Visualizing Textual Data."

| Analytical layer | Indicator | Result | Qualification |
|---|---|---|---|
| | Transitional period, 2017–2020 | 60 articles (3.79%) | Period boundary derived from the trend-topic and thematic-evolution outputs. |
| | Recent acceleration period, 2021–2026 | 1,486 articles (93.75%) | Includes partial year coverage for 2026. |
| **TALL textual analysis** | Random abstract sample | 792 abstracts (49.97%) | The sample was nested within a complete bibliometric corpus. |
| | Year-based analytical units | 17 | The sampled abstracts were aggregated by publication year; these units should not be interpreted as 17 articles. |
| | Textual coverage | 172,970 tokens; 7,635 lemmas; 7,437 sentences | These values refer to the pre-processed abstract corpus reported by the TALL. |

The corresponding-author analysis identified representation across 34 Asian countries or territories under the applied regional classification. The output was unevenly distributed, with China accounting for 360 corresponding-author articles, followed by India (97), Saudi Arabia (95), Türkiye (93), Indonesia (92), Hong Kong (82), and Malaysia (79). These figures describe authorship patterns rather than the geographical settings of the reported studies.

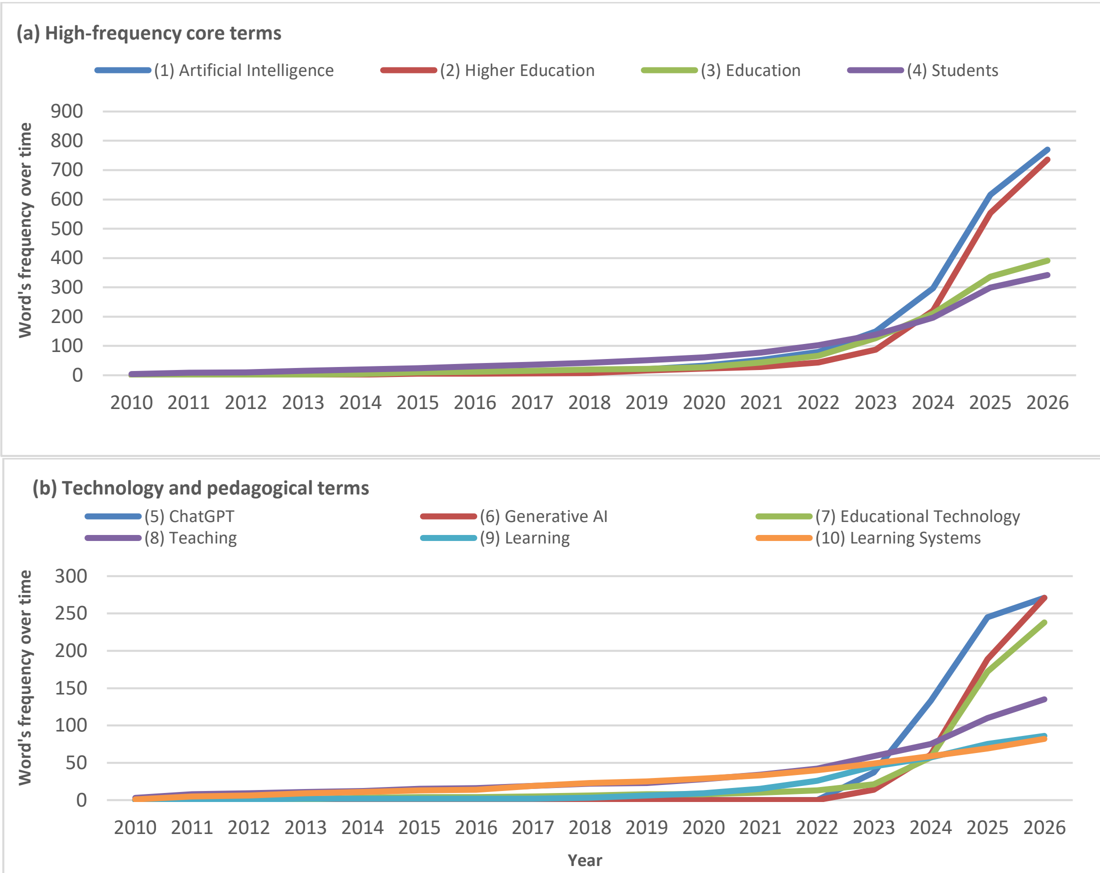


**Figure 1**. Cumulative frequency of leading keywords in AI-in-education research involving Asian-affiliated scholars, 2010–2026. Values represent cumulative keyword occurrences. *Source: Authors' modification and visualisation based on the Words' Frequency over Time output generated by Biblioshiny from the corpus of 1,585 Scopus articles.*[32]

[32] Aria and Cuccurullo, "Bibliometrix : An R-Tool for Comprehensive Science Mapping Analysis."

## 1. Conceptual communities of AI-related educational research

The 50-node keyword co-occurrence network identified three interconnected conceptual communities (Figure 2), namely, which together organised the literature on technological adoption, educational development, and student-facing teaching and learning processes.

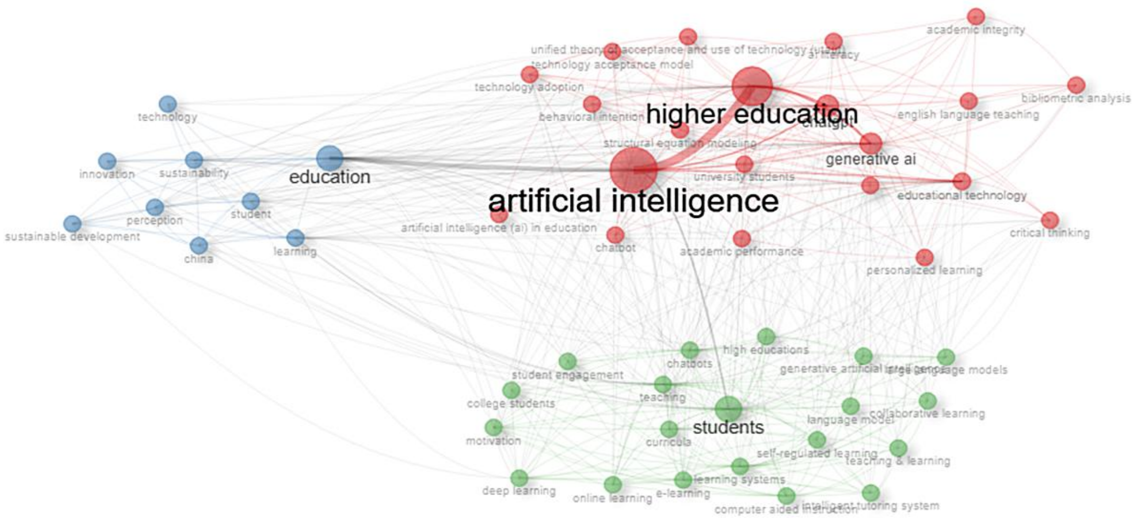


**Figure 2**. Co-word network of the 50 leading merged keywords in AI-in-education research involving Asian-affiliated scholars. *Souce: Biblioshiny analysis*.[33]

The first community (community 1) was centred on *artificial intelligence* and *higher education*, with 770 and 736 occurrences, respectively. These terms were connected with *ChatGPT* and *generative AI* (271 occurrences each), *educational technology* (238), *technology acceptance model* (60), and the *unified theory of acceptance and use of technology* (45). The same community included *AI literacy* (44), *academic integrity* (40), *technology adoption* (36), *ethics* (35), *critical thinking* (31), and *personalised learning* (30). Its composition places higher education at the intersection of generative technologies, user adoption, and emerging responsible-use concerns. However, AI literacy, academic integrity, and ethics remain embedded within this technology-led community rather than forming a separate conceptual structure.

The second community (community 2) connected *education* (391 occurrences) with *learning* (86), *sustainability* (61), *students* (49), and *sustainable development* (44). Less frequent terms included *China* (35), *innovation* and *academic performance* (22 each), *perceptions* (21), *curricula* (20), and *knowledge* (19). This community situates AI-related research within broader educational-development concerns. Sustainability and innovation were associated with learning and curriculum; however, this grouping contained fewer highly connected terms than the technology- and student-oriented communities.

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[33] Aria and Cuccurullo.

The third community (community 3) was organised around *students* (342 occurrences) and *teaching* (135). These terms were linked to *learning systems* (82), *chatbots* (64), *deep learning* (61), *computer-aided instruction* (59), *e-learning* (55), and *intelligent tutoring systems* (52). The community also included *curricula*, *motivation*, *self-regulated learning*, *student engagement*, *online learning*, and *collaborative learning*. Therefore, it brought together earlier instructional technologies and more recent AI applications through a predominantly student-facing educational orientation. The presence of motivation, engagement, and self-regulation indicates attention to learner-related processes, although these constructs were less frequent than technological and institutional terms.

**Table 2**. Educational composition of the three conceptual communities identified by the Biblioshiny co-word analysis.[34]

| Community | Selected leading terms (occurrences) | Educational emphasis | Structural observation |
|---|---|---|---|
| **Commubity 1**: AI, higher education, generative AI, and adoption (*n* = 21 nodes) | Artificial intelligence (770); higher education (736); ChatGPT (271); generative AI (271); educational technology (238); technology acceptance model (60); UTAUT (45); AI literacy (44); academic integrity (40); technology adoption (36); ethics (35); critical thinking (31) | This community connects the field's most frequent technology terms with higher education, technology acceptance and student-facing concerns. The presence of ChatGPT and generative AI indicates that recent technological developments have been incorporated into adoption-oriented higher education discourse. | AI literacy, academic integrity, and ethics occur within the larger technology-and-adoption community rather than forming an autonomous, responsible-use community. |
| **Commubity 2**: Education, learning, and sustainability (*n* = 9 nodes) | Education (391); learning (86); sustainability (61); student (49); sustainable development (44); China (35); innovation (22); technology (22); perception (21) | This community associates education and learning with sustainability, innovation and sustainable development. Its composition places AI-related educational research within the broader discourse of institutional and developmental change. | Sustainability is conceptually connected to education and learning, although explicit pedagogical mechanisms linking AI to sustainable educational development are less prominent among the leading nodes. |
| **Commubity 3**: Students, teaching, and learning systems (*n* = 20 nodes) | Students (342); teaching (135); learning systems (82); chatbots (64); deep learning (61); computer-aided instruction (59); e-learning (55); intelligent tutoring system (52); large language models (47); curricula (43); motivation (32); student | This community connects student learning and teaching with successive generations of educational technology, ranging from computer-aided instruction and intelligent tutoring systems to chatbots and large-language models. | Students and technological systems occupy more prominent positions than teachers as pedagogical decision makers. Assessment redesign and teacher agency do not appear as leading nodes in this network. |

[34] Aria and Cuccurullo.

| Community | Selected leading terms (occurrences) | Educational emphasis | Structural observation |
|---|---|---|---|
| | engagement (30); self-regulated learning (28) | Motivation, engagement, and self-regulated learning are the principal learner-processes. | |

Across the three communities, higher education and students constituted the principal educational settings and actors through which AI was discussed in the literature. Teachers were visible through teaching-related terms, but teacher agency did not form an independent community in the data. Likewise, assessment appeared in the wider keyword structure but did not organise a leading cluster. Therefore, the network mapped a field in which pedagogical concerns were present and internally connected, but remained closely tied to technological systems, adoption constructs, and higher-education use.

## 2. Thematic positioning of educational priorities

For reporting, related communities in the broader thematic map were synthesised into three macro-level clusters: artificial intelligence, students, and education (Figure 3). Their relative centrality and density indicate different structural roles. The *artificial intelligence* cluster had the highest Callon centrality (3.118) and the greatest cumulative frequency (3,660), but the lowest density (12.077).

Therefore, it was the most strongly connected theme across the field, while its internal composition remained comparatively heterogeneous. In addition to AI and higher education, it incorporates generative AI, ChatGPT, educational technology, adoption models, AI literacy, academic integrity, and ethics. Its position indicates that technological development and institutional adoption serve as the main conceptual bridge between otherwise distinct educational concerns.

The student cluster recorded the highest density (18.435), centrality (2.565), and cumulative frequency (1, 711). Its internal structure connects students with teaching, learning systems, curricula, motivation, self-regulated learning, and technology-supported learning environments. Student-oriented research formed the most internally cohesive educational area relative to other clusters. The *education* cluster had a density of 14.347, centrality of 1.434, and cumulative frequency of 1,199. It connects learning with sustainability, sustainable development, innovation, curriculum, knowledge and academic performance.

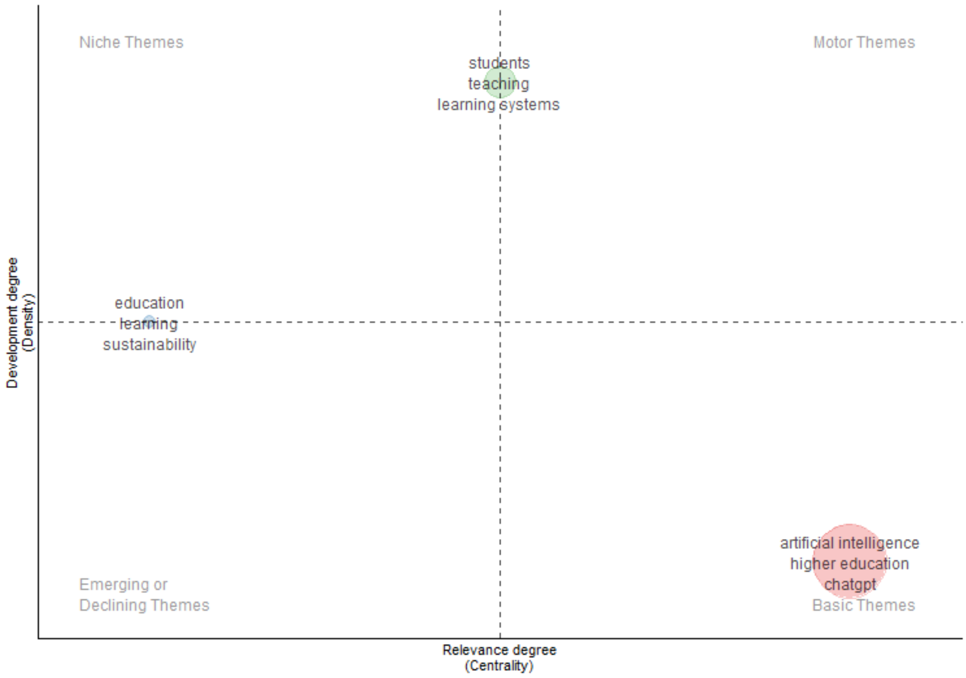


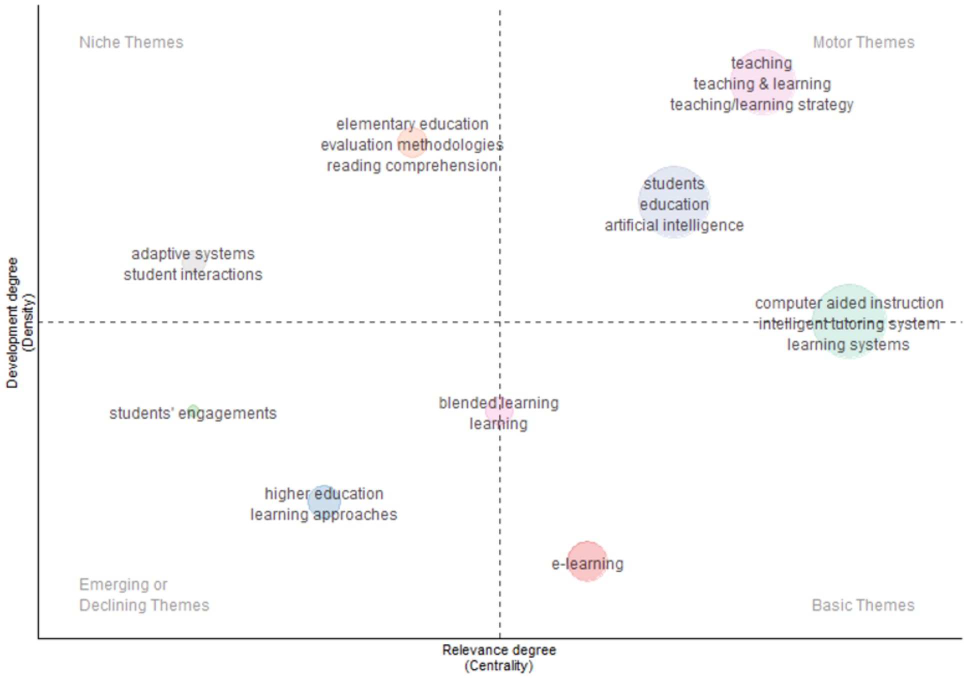

**Figure 3**. Thematic map of AI-in-education research involving Asian-affiliated scholars. *Source: Biblioshiny analysis*.[35]

Its lower centrality suggests that these broader educational-development concerns are less extensively connected to the field's dominant technology- and adoption-oriented structure. The map thus shows that education-focused concepts were present, but technological innovation remained the principal organising centre.

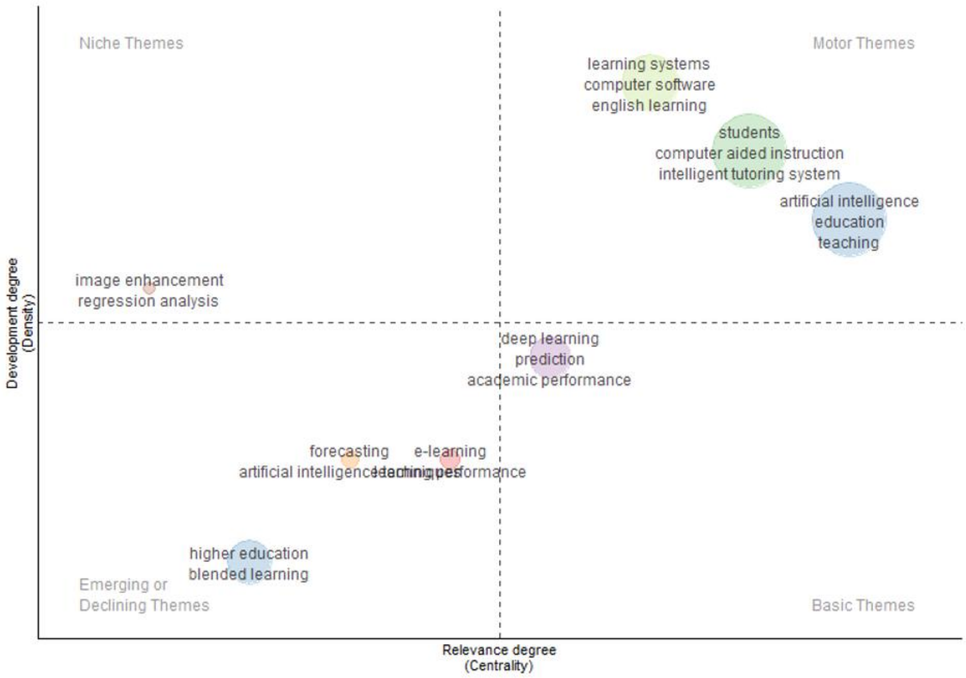
## 3. Changing thematic positions across the three periods

The period-specific thematic maps revealed changes in thematic composition and structural positioning across the foundational (2010–2016), transitional (2017–2020), and recent acceleration (2021–2026) periods (Figure 4). Motor themes combined relatively high centrality and density; basic themes were broadly connected but less internally cohesive; and niche themes were internally connected but comparatively peripheral. These positions are relational indicators rather than measures of research quality, thematic maturity or educational effectiveness.

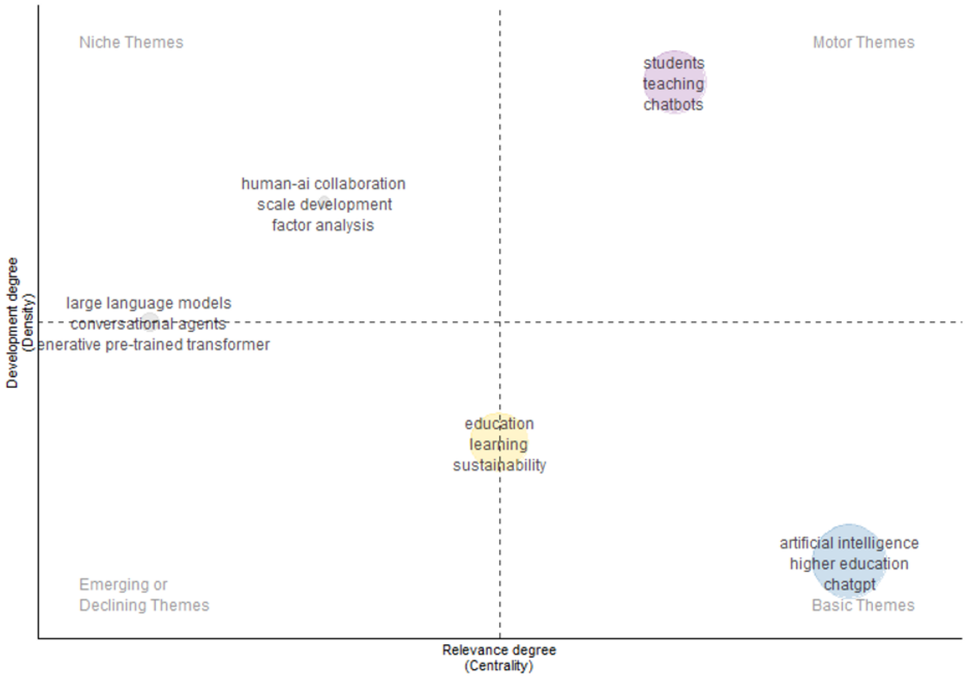
[35] Aria and Cuccurullo.




**(a)** Foundational period (2010–2016)




**(b)** Transitional period (2017–2020)




**(c)** Recent acceleration period (2021–2026)

**Figure 4**. Period-specific thematic maps showing thematic evolution across the foundational, transitional, and recent acceleration periods. Panels represent **(a)** 2010–2016, **(b)** 2017–2020, and **(c)** 2021–2026. Themes are positioned according to Callon centrality on the horizontal axis and Callon density on the vertical axis. Dashed lines indicate the median thresholds, and the bubble size represents the relative theme frequency. The maps support a descriptive comparison of thematic positions but do not demonstrate direct thematic lineage or causal succession. The final period included partial 2026 coverage up to 23 May. *Souce: Biblioshiny analysis.*[36]

During 2010–2016, the motor quadrant contained teaching and teaching–learning strategies, students, education, and artificial intelligence, and computer-aided instruction, intelligent tutoring systems, and learning systems. The instructional systems theme lay close to the median density boundary, while e-learning occupied the basic-theme quadrant. Elementary education and adaptive systems formed specialised niche themes, whereas higher education and learning approaches remained comparatively peripheral. The foundational configuration was therefore organised principally around instructional systems and teaching applications rather than higher education as an institutional context.

Between 2017 and 2020, three motor themes connected learning systems with computer software and English learning, students with computer-aided instruction and intelligent tutoring systems, and artificial intelligence with education and teaching. Deep learning, prediction, and academic performance appeared close to the centrality and density boundaries, indicating a growing but not strongly consolidated, data-driven orientation. E-learning, forecasting, higher education, and blended learning were less central. This transitional configuration broadened the AI vocabulary of the field while retaining continuity with student-oriented instructional technologies.

[36] Aria and Cuccurullo.

During 2021–2026, students, teaching, and chatbots were the principal motor themes. Artificial intelligence, higher education, and ChatGPT constituted the largest basic theme; it was strongly connected with the wider field but had a comparatively low internal density. Education, learning, and sustainability occupied another basic position close to the centrality threshold. Human–AI collaboration, scale development, and factor analysis formed a niche theme, suggesting internal specialisation but limited integration with a wider conceptual structure.

Large language models, conversational agents, and generative pre-trained transformers were positioned on the less-central side of the recent map, close to the median density threshold. Therefore, they were visible but still peripheral relative to the student-facing motor theme and the central AI–higher education–ChatGPT basic theme. Neither large language models nor human–AI collaboration have yet become an organising bridge across the wider field. Across the three maps, teaching remained structurally prominent, but its associations shifted from instructional strategies and systems to students and chatbots. Higher education moved from a peripheral position in the first two periods to a central theme associated with AI and ChatGPT in the recent period. The comparison therefore indicates conceptual layering rather than the disappearance of earlier technologies: generative and human–AI concerns were added to an established instructional foundation, while pedagogical mechanisms, teacher agency, assessment redesign, and responsible-use competencies did not emerge as independent thematic structures.

## 4. Abstract-level elaboration of educational meanings

TALL was applied to a random sample of 792 abstracts, representing 49.97% of the bibliometric corpus. Textual analysis was used to elaborate on the educational meanings associated with the Biblioshiny structures, not to validate or reclassify them. At the lexical level, *artificial intelligence* was the most frequent expression, followed by *student*, *learning*, *study*, and *education*. Teaching- and implementation-related vocabulary included *teacher*, *design*, *adoption*, *performance*, *integration*, *engagement*, *skill*, *intention*, *support*, *assessment*, *feedback*, *literacy*, and *policy*. The prominence of *students* relative to *teachers* was consistent with the student- and higher-education concentration observed in the bibliometric networks.

**Table 3**. Abstract-level elaboration of the bibliometric structures in the TALL subsample analysis. *Source: TALL topic modelling*.[37]

| Topic & interpretive label | Selected discriminating terms (β) | Educational meaning in the abstracts | Bibliometric structure elaborated |
|---|---|---|---|
| **Topic 1**: University students' use and adoption | Use (.161); student (.124); university (.052); model (.052); perceive (.044); factor (.040); adoption (.036); intention (.029) | The topic centres on university students' use of AI and the factors associated with perceptions, adoption, and behavioural | Community 1 elaborated on the connection between higher education, students, the technology acceptance model, UTAUT, |

[37] Aria et al., "TALL: Text Analysis for All–an Interactive R-Shiny Application for Exploring, Modeling, and Visualizing Textual Data."

| Topic & interpretive label | Selected discriminating terms (β) | Educational meaning in the abstracts | Bibliometric structure elaborated |
|---|---|---|---|
| | | intentions. This reflects substantial empirical interest in explaining whether and why students accept AI-related technologies. | technology adoption, and behavioural intention. |
| **Topic 2**: Learning design, teaching, and learner engagement | Learning (.189); student (.128); design (.053); teaching (.052); group (.050); system (.041); engagement (.032); GenAI (.031); improve (.030); support (.029) | The topic connects AI and generative AI with the design of teaching and learning systems, student engagement, group learning and instructional support. Terms such as *improve* and *support* indicate how educational functions were framed in abstracts. | Community 3 elaborates on how systems-oriented terms are connected in the abstracts with learning design, teaching, engagement, and instructional support. |
| **Topic 3**: Educational development, research, and digital skills | Education (.176); research (.071); analysis (.071); intelligence (.063); academic (.062); artificial intelligence (.054); development (.042); digital (.033); skill (.032) | This topic frames AI in relation to educational research, academic development, digital skills, and the analytical or conceptual frameworks used to examine educational changes. | Adds digital-skill and development vocabulary to the broader education and sustainability community and to the education macro-theme identified in the thematic map. |
| **Topic 4**: Teachers, language education, ethics, and AI literacy | Artificial intelligence (.321); tool (.059); teacher (.050); language (.038); ethical (.035); English (.028); chatbot (.026); literacy (.025); generative (.024) | This topic makes teachers more visible in discussions of AI tools, chatbots, language education, ethical concerns and literacy. However, teacher-related terms are mainly connected with the use and interpretation of technological tools rather than a distinct discourse on teacher agency. | Community 1 elaborated on AI literacy and ethics terms while revealing teacher- and language-related meanings that were less prominent in the bibliometric network. |
| **Topic 5**: ChatGPT-specific opportunity and impact framing | ChatGPT (.082); technology (.082); educational (.074); enhance (.043); provide (.042); research (.040); potential (.035); impact (.034); human (.034); future (.028) | This topic frames ChatGPT primarily in terms of its potential educational applications, anticipated impact, and future possibilities. The accompanying benefit-oriented vocabulary indicates an opportunity-focused abstract discourse rather than demonstrated effectiveness. | Elaborates on the recent prominence of ChatGPT and generative AI in Community 1 and in the recent 2021–2026 period. |

The five-topic model provided further differentiation. The first topic connected student and university use with perception, adoption, intention, influence, and technology acceptance factors. The second linked learning and teaching with design, systems, engagement, generative AI, learner support and improvement. The third combined education with research, development, digital skills, frameworks and challenges. The fourth theme brought together AI tools, teachers, language, ethics, chatbots, literacy, and generative technologies. The fifth centred on ChatGPT, educational technology, enhancement, potential, impact, and future applications.

These topics clarify the meanings contained within the bibliometric communities. Adoption was discussed primarily through student and university use, pedagogical integration was articulated through learning design, engagement, and support, and responsible use appeared through teacher-related, ethical, and literacy vocabulary. Assessment and feedback were present, but neither formed a dominant textual topic. Moreover, the frequent use of terms such as *enhance*, *support*, *improve*, and *potential* indicates benefit-oriented framing within the abstracts. This language records how the literature presented AI's educational relevance of AI; however, it does not establish that the reported technologies improved learning outcomes in practice.

## Discussion

Taken together, the findings indicate a reorientation rather than merely an expansion of AI-in-education research involving Asian-affiliated scholars. The mapped literature moved from a configuration anchored in instructional systems to one increasingly organised around generative AI, student-facing applications, technology adoption, and emerging human–AI interaction. This reorientation has not been accompanied by an equally integrated treatment of pedagogical mechanisms, teacher agency, assessment redesign or responsible-use competencies. The abstract-level analysis elaborates this interpretation by showing how adoption, enhancement, support, and future potential are articulated in the literature; however, it does not establish whether the technologies concerned improve education in practice.

### 1. From instructional systems to generative and adoption-oriented research

The period-specific maps (Figure 4) revealed three overlapping configurations. From 2010 to 2016, instructional systems, teaching strategies, students, education, and AI occupied motor positions, while higher education remained peripheral. From 2017 to 2020, computer-aided instruction and intelligent tutoring systems persisted within a student-oriented motor theme alongside a broader AI–education–teaching configuration. From 2021 to 2026, students, teaching, and chatbots formed the principal motor theme, whereas AI, higher education, and ChatGPT formed a highly central but less cohesive basic theme.

This pattern indicates conceptual layering rather than displacement: generative and conversational technologies were added to an established systems-oriented foundation, consistent with reviews showing the coexistence of tutoring, adaptive, predictive, and generative applications.[38] The movement of higher education from the periphery to the AI–higher education–ChatGPT basic theme is analytically consequential. High centrality and low density indicate broad field-level connectivity but weaker internal cohesion.[39] In contrast, the motor position of students, teaching, and chatbots identifies a more cohesive student-facing application focus; it does not, by itself, establish learner-centred pedagogy or demonstrate learning effects.[40]

The peripheral large-language-model theme and niche human–AI-collaboration theme further constrain claims of transformation: both are visible specialisations, yet neither structures the wider field. This is consistent with accounts of LLM opportunities and risks for students and teachers,[41] the limited empirical examination of pedagogical implementation,[42] and the strongly benefit-oriented claims surrounding the use of ChatGPT in higher education.[43] The evidence therefore indicates changing research priorities and structural positions, not an equivalent transformation of the educational practice.

## 2. The dominance of higher education and student-focused research

The prominence of higher education and students is one of the field's clearest structural features. Higher education is closely connected with AI, ChatGPT, generative AI, and technology adoption models, whereas the student macro-theme has the highest internal density. Therefore, student-related research is comparatively cohesive within the map. However, density denotes internal conceptual connectedness, not educational quality or intervention effectiveness.[44]

Abstract-level topics associated students with use, universities, perceptions, adoption factors, behavioural intention, engagement, and system-supported learning. They are positioned primarily as AI users or adopters, mirroring the wider concentration of higher-education acceptance research on technological and individual determinants.[45] Less evidence positions students as participants in co-design, critical evaluation, or governance. This gap is consistent with reviews finding limited end-user involvement in AIED system design and

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[38] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Chen, Tsang, and Wu, "When Text Mining Meets Science Mapping in the Bibliometric Analysis: A Review and Future Opportunities"; Crompton and Burke, "Artificial Intelligence in Higher Education: The State of the Field."
[39] Angelelli et al., "Conceptual Structure and Thematic Evolution in Partial Least Squares Structural Equation Modeling Research."
[40] Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education"; Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies."
[41] Kasneci et al., "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education."
[42] Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies."
[43] Lasse X Jensen et al., "Generative AI and Higher Education: A Review of Claims from the First Months of ChatGPT," *Higher Education* 89, no. 4 (April 15, 2025): 1145–61, https://doi.org/10.1007/s10734-024-01265-3.
[44] Angelelli et al., "Conceptual Structure and Thematic Evolution in Partial Least Squares Structural Equation Modeling Research."
[45] Dinara Farhatovna Mukhamedkarimova and Madina Maximovna Umurkulova, "Factors Contributing to Higher Education Students' Acceptance of Artificial Intelligence: A Systematic Review," *European Journal of Educational Research* 14, no. 4 (September 24, 2025): 1373–88, https://doi.org/10.12973/eu-jer.14.4.1373.

calling for stronger student participation.[46] Therefore, student-focused research should not be equated with learner-centred pedagogy; research can examine students frequently while organising its questions around acceptance rather than the cognitive, social, and pedagogical mechanisms of learning.

This pattern continues to raise concerns identified in recent syntheses of AI in higher education, including application-led research, limited conceptual grounding, and insufficient ethical, contextual, pedagogical, and interdisciplinary attention.[47] The present findings show that these concerns remain relevant in scholarship involving Asian-affiliated authors despite their expanded technological vocabulary. University concentration also narrows the visible educational settings in the field. School education, vocational learning, teacher education, and lifelong learning do not occupy comparable positions in the main conceptual framework. Because eligibility was determined through affiliations across 34 Asian countries and territories, this pattern should not be read as a unified account of "Asian education". It represents a transnational scholarly configuration spanning diverse national and institutional contexts, not evidence that Asian education systems share the same priorities or conditions.

### 3. Pedagogy, teacher agency, and assessment remain incompletely integrated

Teaching, learning, curricula, motivation, engagement, and self-regulated learning appeared in the co-word network, confirming that the field is not exclusively technological. However, these concerns are mainly connected with students and learning systems rather than an independent account of pedagogical decision-making. Educational vocabulary alone does not explain how AI alters learning design, sequencing, mediation, or evaluation; such claims require explicit pedagogical models and implementation evidence.[48]

Teacher agency illustrates this imbalance in the following ways. Teachers are not a leading organising node in the bibliometric network, although TALL makes them visible in abstracts concerning AI tools, language education, chatbots, ethics, and literacy. Therefore, teachers are present discursively without yet organising the field structurally. Abstracts also associate them more often with using or responding to tools than with controlling instructional objectives, task design, evidence of learning, or boundaries for AI use in education. This distinction is important because teacher agency entails pedagogical judgement and authority over the design and adaptation of AI-supported activities, not tool adoption alone.[49]

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[46] Riordan Alfredo et al., "Human-Centred Learning Analytics and AI in Education: A Systematic Literature Review," *Computers and Education: Artificial Intelligence* 6 (June 2024): 100215, https://doi.org/10.1016/j.caeai.2024.100215; Jensen et al., "Generative AI and Higher Education: A Review of Claims from the First Months of ChatGPT."

[47] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour"; Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education"; Crompton and Burke, "Artificial Intelligence in Higher Education: The State of the Field."

[48] Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies"; Chiu et al., "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education."

[49] Peter Kahn et al., "Teacher Agency and Generative Artificial Intelligence: Teaching in Higher Education as a Responsive, Cultural Activity," *Learning, Media and Technology*, October 18, 2025, 1–12, https://doi.org/10.1080/17439884.2025.2575993; Yu Ju Lan and Nian Shing Chen, "Teachers' Agency in the Era of LLM and

The assessment followed a similar pattern. It appears in abstract-level vocabulary but does not form a leading bibliometric community, whereas academic integrity is prominent within the generative AI- and adoption-oriented communities. Consequently, assessment may be framed mainly as a means of detecting or regulating inappropriate use. However, AI also changes what should be assessed, how learning can be evidenced, and when performance should be human, AI-assisted, or independent. Therefore, recent work argues for redesign centred on validity, authenticity, learning processes, and future capabilities rather than technological protection alone.[50]

Future research should specify and test the mechanisms through which AI supports learning, including feedback, explanations, practice, dialogue, reflection, collaboration, and metacognitive regulation.[51] Teacher agency should be examined through design choices, professional judgement, monitoring, and revision of AI-supported activities, while assessment studies should test the transparency and alignment among AI use, task conditions, and intended learning outcomes.

## 4. Responsible AI as an embedded educational concern

AI literacy, academic integrity, ethics, and critical thinking occur within the principal AI–higher-education community. Their location is analytically significant. Proximity to generative AI and adoption suggests that responsible-use concerns are entering the field's mainstream, and dependence on the larger technology-led community indicates that they have not formed an autonomous, internally integrated educational theme. Therefore, the more cautious interpretation is that responsible use is visible but unevenly incorporated.

TALL elaborates on this structure by linking teachers, AI tools, language education, ethics, chatbots, and literacy within one abstract-level topic. This makes the actors and contexts of responsible use more explicit than the keyword network but provides limited evidence of consistent integration with curricula, assessment, teacher professional learning, or institutional capacity. Reviews of AI literacy and teacher education similarly call for technical knowledge to be connected with pedagogy, critical evaluation and ethical practice.[52] Responsible use may otherwise become a response added after adoption, rather than a condition governing it. Accordingly, AI literacy should be treated as a competence, not merely risk awareness. It encompasses understanding AI, applying it, evaluating and creating it, and

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Generative AI: Designing Pedagogical AI Agents," *Educational Technology & Society* 27, no. 1 (January 1, 2024): i–xviii, https://doi.org/10.30191/ETS.202401_27(1).PP01.

[50] Swiecki et al., "Assessment in the Age of Artificial Intelligence"; Qi Xia et al., "A Scoping Review on How Generative Artificial Intelligence Transforms Assessment in Higher Education," *International Journal of Educational Technology in Higher Education* 21, no. 1 (May 24, 2024): 40, https://doi.org/10.1186/s41239-024-00468-z.

[51] Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies"; Wang Xiaoyu, Zamzami Zainuddin, and Chin Hai Leng, "Generative Artificial Intelligence in Pedagogical Practices: A Systematic Review of Empirical Studies (2022–2024)," *Cogent Education* 12, no. 1 (December 31, 2025), https://doi.org/10.1080/2331186X.2025.2485499.

[52] Ng et al., "Conceptualizing AI Literacy: An Exploratory Review"; Katarina Sperling et al., "In Search of Artificial Intelligence (AI) Literacy in Teacher Education: A Scoping Review," *Computers and Education Open* 6 (June 2024): 100169, https://doi.org/10.1016/j.caeo.2024.100169.

addressing ethical issues.[53] UNESCO's teacher framework similarly integrates a human-centred mindset, AI ethics, foundations and applications, AI pedagogy, and professional learning.[54] Critical thinking is therefore part of evaluating outputs, recognising limitations, and making pedagogically defensible decisions rather than an adjacent outcome.[55]

Ethics must extend beyond privacy, bias, and academic misconduct. Ethical AIED concerns pedagogical choices, teacher roles, assessment, human agency, cognition, resource allocation, and power relations.[56] Because the affiliation-based corpus represents substantial institutional diversity, no common implementation model can be inferred from it. Future research should examine how responsible-use competencies are enacted under differing curricular, linguistic, regulatory, and infrastructural conditions, including how institutional policies enable or constrain educational practice.[57]

## 5. Educational contribution and research priorities

The principal contribution of this study is the identification of uneven educational integration amid technological expansion. The field is not moving from absent to present pedagogy or irresponsible to responsible AI. Instead, technological capability, pedagogical enactment, and responsible institutional conditions exhibit different levels of conceptual integration. AI and higher education provide the central organising structure; student research supplies a cohesive empirical focus; and pedagogy, teacher agency, assessment, and responsible-use competencies remain distributed across these structures. Future research should address three questions: what an AI system can do, through which pedagogical mechanisms it may support learning, and under which responsible conditions it should be used. Doing so would strengthen conceptual grounding, pedagogically informed implementation, and ethical rigour while moving beyond studies terminating with perceived usefulness, behavioural intention, or general acceptance.[58] Adoption remains relevant but should be linked to instructional design, teacher judgement, learning processes, assessment evidence, and equitable participation.

Human–AI collaboration offers one route towards these connections, although its niche position marks it as specialised and peripheral. Studies could examine how roles are distributed among teachers, students, and AI; where human oversight is required; and which

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[53] Ng et al., "Conceptualizing AI Literacy: An Exploratory Review."

[54] UNESCO, Fengchun Miao, and Mutlu Cukurova, *AI Competency Framework for Teachers*, *UNESDOC Digital Library* (UNESCO, 2024), https://doi.org/10.54675/ZJTE2084.

[55] Yoshija Walter, "Embracing the Future of Artificial Intelligence in the Classroom: The Relevance of AI Literacy, Prompt Engineering, and Critical Thinking in Modern Education," *International Journal of Educational Technology in Higher Education* 21, no. 1 (February 26, 2024): 15, https://doi.org/10.1186/s41239-024-00448-3.

[56] Yao Fu and Zhenjie Weng, "Navigating the Ethical Terrain of AI in Education: A Systematic Review on Framing Responsible Human-Centered AI Practices," *Computers and Education: Artificial Intelligence* 7 (December 2024): 100306, https://doi.org/10.1016/j.caeai.2024.100306; Holmes et al., "Ethics of AI in Education: Towards a Community-Wide Framework."

[57] Yueqiao Jin et al., "Generative AI in Higher Education: A Global Perspective of Institutional Adoption Policies and Guidelines," *Computers and Education: Artificial Intelligence* 8 (June 2025): 100348, https://doi.org/10.1016/j.caeai.2024.100348; UNESCO, Miao, and Cukurova, *AI Competency Framework for Teachers*.

[58] Belkina et al., "Implementing Generative AI (GenAI) in Higher Education: A Systematic Review of Case Studies"; Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour."

knowledge and judgements should remain under human control. Such work would operationalise complementary regulation and agency rather than automation, providing pedagogical content to international human-centred guidance.[59]

The abstracts' benefit-oriented vocabulary requires careful interpretation and analysis. *Enhance*, *support*, *improve*, and *potential* reveal how authors position AI but do not demonstrate learning gains or effectiveness. Studies should distinguish between anticipated benefits and observed outcomes and report their conditions.[60] For example, chatbot effects vary by educational level and intervention duration.[61] Sustainability requires the same caution: conceptual association does not establish contribution, while evidence remains dominated by conceptual and small-scale studies.[62] By prioritising mechanisms, actors, assessment, outcomes, and responsible conditions, educational research can move from documenting technological expansion to explaining when AI use becomes pedagogically meaningful.

## 6. Limitations

Several limitations delimit this interpretation. The corpus comprised English-language journal articles indexed in Scopus in selected subject areas. Publications indexed elsewhere, written in other languages, or issued as conference papers, books, or reports were excluded. Because databases differ in journal coverage, the mapped structure is Scopus-bounded rather than exhaustive.[63] Affiliation-based eligibility identifies scholarships involving authors from institutions in 34 Asian countries and territories. It establishes neither the research location nor the collective representativeness of Asian educational systems. Therefore, national or institutional differences cannot be inferred from the aggregated structure.

The 2026 coverage extends only to 23 May and the recent acceleration period contains substantially more publications than the earlier periods. Period-specific maps consequently describe conceptual attention under unequal publication volumes; they establish neither causal stages nor differences in research quality. Bibliometric analysis depends on author keywords, Keywords Plus, indexing practices, and frequency thresholds. Terminological variation and thresholding may reduce the visibility of less frequent or emerging concerns

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[59] Kahn et al., "Teacher Agency and Generative Artificial Intelligence: Teaching in Higher Education as a Responsive, Cultural Activity"; Fengchun Miao and Wayne Holmes, *Guidance for Generative AI in Education and Research*, *UNESDOC Digital Library* (UNESCO, 2023), https://doi.org/10.54675/EWZM9535; Inge Molenaar, "The Concept of Hybrid Human-AI Regulation: Exemplifying How to Support Young Learners' Self-Regulated Learning," *Computers and Education: Artificial Intelligence* 3 (2022): 100070, https://doi.org/10.1016/j.caeai.2022.100070; Inge Molenaar, "Towards Hybrid Human-AI Learning Technologies," *European Journal of Education* 57, no. 4 (December 23, 2022): 632–45, https://doi.org/10.1111/ejed.12527.

[60] Margaret Bearman, Juliana Ryan, and Rola Ajjawi, "Discourses of Artificial Intelligence in Higher Education: A Critical Literature Review," *Higher Education* 86, no. 2 (August 24, 2023): 369–85, https://doi.org/10.1007/s10734-022-00937-2.

[61] Bond et al., "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour."

[62] Ben Kei Daniel, Nataliya Podgorodnichenko, and Sarah Carr, "A Scoping Review of AI for Sustainability and Sustainable AI in Higher Education," *Discover Computing* 29, no. 1 (January 27, 2026): 48, https://doi.org/10.1007/s10791-025-09861-2.

[63] Vivek Kumar Singh et al., "The Journal Coverage of Web of Science, Scopus and Dimensions: A Comparative Analysis," *Scientometrics* 126, no. 6 (June 26, 2021): 5113–42, https://doi.org/10.1007/s11192-021-03948-5.

because bibliometric maps remain sensitive to data selection and analytical decisions.[64] Centrality and density represent relational position and internal connectedness, not thematic maturity, pedagogical value, or educational effectiveness.

TALL analysed a random sample of 792 abstracts rather than full texts. Abstracts represent research framing but cannot fully reveal instructional design, implementation conditions, assessment practices, or learning outcomes; abstract- and full-text-based topic models can produce different representations.[65] Topic labels were interpretatively assigned, and benefit-oriented terms represented the authors' framing rather than demonstrated effects. Textual analysis elaborates on, but does not independently validate, bibliometric structures. Within these boundaries, this study maps conceptual attention and association rather than the effectiveness of AI-supported education.

## CONCLUSION

This study mapped the changing educational priorities in AI-related scholarship involving Asian-affiliated authors between 2010 and 2026. The findings indicate a reorientation from research centred on computer-aided instruction, intelligent tutoring systems, and learning systems towards a field increasingly organised around generative AI, ChatGPT, technology adoption, and emerging human–AI interaction. This development represents conceptual layering rather than the disappearance of earlier instructional technology.

Higher education and students provide the most prominent educational contexts and actors in this structure. However, students are frequently positioned as users or adopters, while pedagogical mechanisms, teacher agency, and assessment redesign remain less integrated. AI literacy, academic integrity, ethics, and critical thinking are increasingly visible but remain embedded within the broader technology-and-adoption discourse rather than constituting a distinct responsible AI structure. The abstract-level analysis elaborates on these patterns by revealing strong attention to adoption, engagement, instructional support, teachers, and anticipated benefits. Nevertheless, its benefit-oriented vocabulary reflects how AI is framed, not evidence that its use improves learning.

This study contributes to educational research by showing that the rapid expansion of AI-related scholarship has produced uneven integration between technological capability, pedagogical enactment, and responsible institutional conditions. Addressing this imbalance requires research that connects what AI can perform with how learning is designed, how teachers exercise professional judgement, how assessment provides valid evidence, and how students develop responsible-use competencies. Because the corpus represents affiliations across diverse Asian countries and territories, these priorities should be investigated within

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[64] Naveen Donthu et al., "How to Conduct a Bibliometric Analysis: An Overview and Guidelines," *Journal of Business Research* 133 (September 2021): 285–96, https://doi.org/10.1016/j.jbusres.2021.04.070.

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specific educational and institutional contexts in the future. Therefore, the next stage of AI-in-education research should be judged not by technological novelty or adoption alone, but by the quality of its pedagogical mechanisms, human agency, and educational evidence.

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