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# Emerging Trends of Artificial Intelligence in Education (2021–2026): A Bibliometric Analysis of Curriculum and Vocational Education Transformation

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***Abstract***

*Artificial intelligence (AI) increasingly reshaped educational practices, prompting growing scholarly inquiry into its pedagogical, curricular, and environmental implications. However, existing bibliometric reviews of Artificial Intelligence in Education (AIED) predominantly predated the generative AI inflection point and rarely disaggregated vocational education as a distinct theme. This study examined the intellectual structure and thematic evolution of AIED research published between 2021 and 2026, focusing on how curriculum development and vocational education transformation were represented within the field. Bibliographic data were retrieved from Scopus using the query "Artificial Intelligence" AND "Education" across title, abstract, and keyword fields, yielding 420 initial records. Following a four-stage Identification-Screening-Eligibility-Inclusion process, 107 peer-reviewed journal articles were retained. Publication output rose from five articles annually in 2021-2022 to 55 in 2025, with 83.2% of the dataset concentrated in 2023-2025, confirming a measurable post-generative AI acceleration. Arts and Humanities (45.0%) and Social Sciences (35.0%) dominated the disciplinary distribution, while China and the United States jointly led geographical output. Keyword co-occurrence mapping identified four clusters, with vocational education and training co-anchoring a cluster alongside deep and reinforcement learning, indicating an established rather than emergent research domain. This study offered the first structured mapping of vocational education's position within the post-2023 AIED landscape, informing curriculum developers, researchers, and policymakers.*

**Keywords: Artificial Intelligence in Education, Bibliometric Analysis, VOSviewer, Curriculum Transformation, Vocational Education**



## 1. INTRODUCTION

Artificial intelligence (AI) has become one of the most consequential forces reshaping contemporary education. Machine learning, intelligent tutoring systems, learning analytics, and, since 2022, generative AI have progressively altered how knowledge is produced, transmitted, and assessed, enabling adaptive learning pathways, automated feedback, and AI-assisted instructional design (Teng et al., 2019; Berestova et al., 2022; Wang & Jia, 2023; Budiarto et al., 2024; Zhang et al., 2025). The public diffusion of large language models has intensified this shift, introducing new affordances for personalized learning while provoking debates over academic integrity and the ethical governance of AI-mediated instruction (Ming et al., 2022; Alfarizi et al., 2023; Latifah et al., 2024). AI integration in education is therefore no longer experimental but institutionally embedded, extending the demand for scholarly attention beyond the classroom into how curricula themselves should be redesigned.

This is precisely where the existing AIED literature falls short. Research on AI in education has expanded substantially, examining domains such as intelligent tutoring, adaptive learning, educational data mining, and AI-supported assessment (Paul & Criado, 2020; Haji & Azmani, 2020; Parveen & Ramzan, 2024; Samala et al., 2024; Suyatno et al., 2023). Yet most of this literature remains oriented toward algorithm development and classroom-level implementation rather than the structural and curricular implications of AI adoption at the institutional level (Lampropoulos et al., 2022), a limitation that extends to the bibliometric reviews of the field itself: prior bibliometric studies of AIED have adopted either a broad technological scope spanning many years or a narrow classroom-level focus, offering limited analytical purchase on the transformative period following 2021, when generative AI achieved widespread institutional diffusion (Prasetya et al., 2025). Critically, none systematically disaggregates how curriculum development and vocational education and training (VET) are positioned within the broader AIED knowledge structure. Prasetya et al. (2025) examined AI's role in vocational education specifically but did not situate VET within the wider AIED landscape through co-occurrence mapping; conversely, general AIED bibliometric reviews have not treated vocational education as an analytically distinct theme at all. This is a meaningful omission, since AI-driven labor market transformation is demanding digital literacy, computational reasoning, and adaptive problem-solving competencies that conventional, role-specific VET curricula were not designed to accommodate (Shiohira, 2021; Ahmed et al., 2025; Karwa, 2025; Ghosh & Ravichandran, 2024). Without a structured account of how the AIED literature engages curriculum and vocational transformation together, curriculum developers and policymakers lack a clear evidence base for reform.

The 2021–2026 window was selected to directly address this gap. It spans both the pre-ChatGPT period of incremental AI adoption and the post-2022 generative AI inflection, allowing the study to isolate whether, and how sharply, this technological discontinuity reshaped the field's thematic priorities, a comparison that reviews with longer or pre-2022-bounded windows cannot make. This temporal anchoring is therefore not incidental but central to the study's novelty: it targets exactly the period during which AI-driven curriculum and vocational competency debates intensified globally, yet remain bibliometrically unmapped in relation to one another.

This study addresses this gap through a bibliometric analysis of AIED research published between 2021 and 2026, using Scopus-derived data and VOSviewer-based science mapping to (1) map the growth trajectory and disciplinary distribution of AIED research, (2) identify dominant thematic clusters with specific attention to how curriculum development and vocational education are positioned relative to other AIED themes, and (3) examine the geographical distribution of research contributions and its implications for VET systems in underrepresented regions. In pursuing these objectives, the study offers three contributions distinguishing it from prior work: a bibliometric mapping bounded specifically to the post-2021 generative AI period rather than a broader or earlier window; the first explicit positioning of curriculum development and vocational education within the structural architecture of recent AIED scholarship, rather than as a peripheral theme; and a comparative geographical account identifying underrepresented regions with direct implications for the generalizability of AI-informed vocational curriculum reform. Together, these contributions provide researchers, curriculum developers, and educational policymakers with a focused evidence base for AI-informed curriculum design and vocational education policy.

## 2. RESEARCH METHODOLOGY

This study employed a quantitative bibliometric design to systematically examine the intellectual structure and thematic development of Artificial Intelligence in Education (AIED) research published between 2021 and 2026. Bibliometric analysis enables large-scale science mapping through the statistical examination of publication metadata, citation structures, and keyword co-occurrence networks, thereby revealing patterns of thematic concentration, disciplinary evolution, and emerging knowledge frontiers within a research field (Donthu et al., 2021). The overall data collection and analysis workflow is illustrated in

Figure 1.


**Figure 1. Steps of Bibliometry Analysis**

Bibliographic data were retrieved from the Scopus database, selected on the basis of its extensive and systematically curated coverage of peer-reviewed international journals, its structured citation indexing, and its broad disciplinary scope encompassing education, computer science, and social sciences. Scopus was preferred over alternatives such as Web of Science or Dimensions because its subject-area classification scheme aligns more directly with the interdisciplinary character of AIED research, and its keyword and abstract indexing conventions are well suited to VOSviewer-based co-occurrence mapping. This single-database approach nonetheless constitutes a limitation: Web of Science and Dimensions index partially non-overlapping journal sets and apply different subject classification systems, meaning that publications indexed exclusively outside Scopus, particularly some regional and open-access AIED journals, were not captured in this dataset. Consequently, the findings should be interpreted as representative of the Scopus-indexed AIED literature rather than the field in its entirety, and cross-database replication is identified as a direction for future research.

The search was conducted in January 2026 using the Boolean query ("Artificial Intelligence" AND "Education"), applied simultaneously to the Title, Abstract, and Keyword fields. This two-term query was deliberately kept broad rather than expanded with additional synonymous phrases such as "AI in Education," "Educational AI," or "Intelligent Tutoring Systems." A preliminary comparison search combining these additional terms with the base query was conducted prior to final data collection; this comparison returned a highly overlapping document set, with the marginal additional records concentrated in narrowly technical intelligent-tutoring-system papers that would in any case have been excluded at the inclusion stage for lacking explicit educational application context. The two-term query was therefore retained to preserve conceptual precision and search replicability, while it is acknowledged that this strategy may exclude a small number of studies using only specialized subfield terminology absent the broader keywords.

The article selection process followed a four - stage Identification - Screening - Eligibility - Inclusion framework, consistent with systematic review conventions widely adopted in bibliometric research (Donthu et al., 2021). The overall selection process is illustrated in

Figure 2, and the criteria applied at each stage are summarized in Table 1.

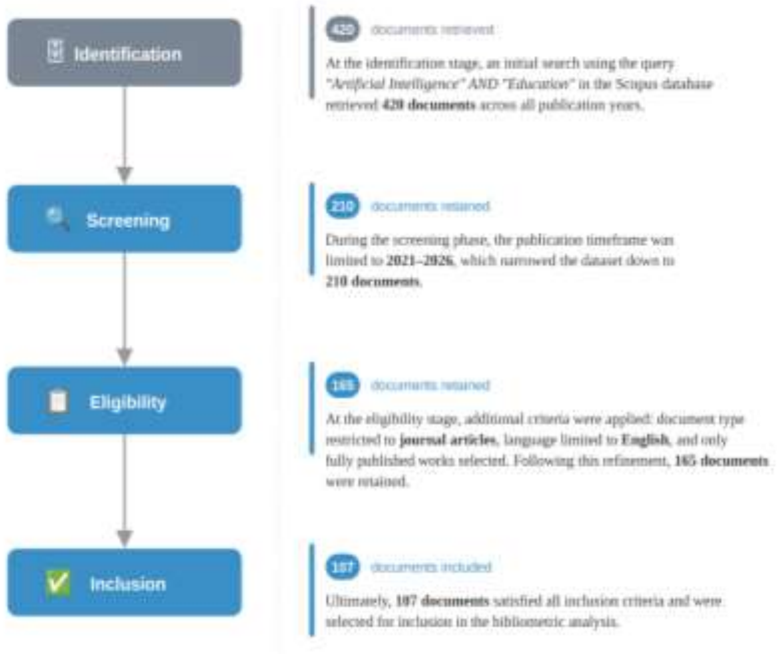


**Figure 2. Article selection process using the Identification–Screening–Eligibility–Inclusion framework**

At the identification stage, the initial search retrieved 420 documents spanning all available publication years. At the screening stage, the dataset was restricted by publication year to 2021–2026, a boundary encompassing both the pre-ChatGPT period of AI adoption and the post-2022 generative AI acceleration, reducing the dataset to 210 documents. At the eligibility stage, document type and language criteria were applied: documents were included only if they were peer-reviewed journal articles published in English, and excluded if they were conference proceedings, book chapters, review articles, editorials, or notes, because these document types differ structurally in peer review standards, citation practices, and bibliometric behavior in ways that could introduce inconsistency into network construction. This stage reduced the dataset to 165 documents. At the inclusion stage, each remaining record was manually assessed for thematic relevance: documents were retained if they addressed the application, integration, or implications of AI within educational systems, including curriculum design, pedagogical practice, learning environments, or vocational education, and excluded if they addressed exclusively technical AI development, such as algorithm design or system architecture optimization, without explicit educational application or context. This assessment was conducted by the first author against the criteria above, with ambiguous cases discussed with the second and third authors until consensus was reached. Following this stage, 107 documents satisfied all criteria and constituted the final bibliometric dataset.

**Table 1**
**Inclusion and Exclusion Criteria by Selection Stage**

| Stage | Discrimination Index | Interpretation |
|---|---|---|
| Screening (year) | Published 2021–2026 | Published before 2021 or after 2026 |
| Eligibility (type/language) | Peer-reviewed journal article; English language | Conference proceedings, book chapters, review |

| | | |
|---|---|---|
| | | articles, editorials, notes; non-English |
| Inclusion (relevance) | Addresses AI application, integration, or implications in educational systems (curriculum, pedagogy, learning environments, vocational education) | Addresses exclusively technical AI development (algorithm design, system architecture) without educational application |

The final dataset was exported from Scopus in CSV format, containing bibliographic metadata including author names, article titles, abstracts, author keywords, publication years, source titles, institutional affiliations, country information, and citation counts. Prior to network construction, data preprocessing was conducted in three steps. First, keyword standardization was performed by converting all author keywords to lowercase and reconciling American and British spelling variants (e.g., "personalized learning" and "personalised learning" were merged into a single term). Second, synonym and variant-term merging was conducted using a manually constructed thesaurus file in VOSviewer, consolidating semantically equivalent terms with differing surface forms (e.g., "AIED" and "artificial intelligence in education"; "VET" and "vocational education and training") into single unified nodes to prevent artificial fragmentation of the co-occurrence network. Third, records with missing author keywords or incomplete abstract fields were flagged and manually reviewed; where keywords could be reliably inferred from the title and abstract, they were added, and records that could not be reliably completed were removed. These steps were necessary to minimize fragmentation in subsequent network construction and to ensure the reliability of co-occurrence mapping.

Bibliometric analysis was conducted in two sequential stages using VOSviewer version 1.6.21, a software tool widely adopted for constructing and visualizing bibliometric networks (van Eck & Waltman, 2010). The first stage comprised performance analysis, examining annual publication growth trajectories, subject area distributions, and country-level research productivity, providing a macro-level account of the field's structural development and geographical characteristics. The second stage comprised science mapping through keyword co-occurrence network analysis. The full counting method was applied, in which each co-occurrence between two keywords within a document is counted with equal weight regardless of how many other keywords appear alongside them; this method was preferred over fractional counting because it better preserves the relative frequency of high-occurrence central terms, which was analytically important for identifying the field's core organizing concepts (van Eck & Waltman, 2010). Association strength normalization was applied to minimize bias arising from differences in overall keyword frequency, following van Eck and Waltman's (2010) demonstration that this method more accurately reflects the relative strength of co-occurrence relationships than raw co-occurrence counts. A minimum co-occurrence threshold of five was set following preliminary sensitivity testing across alternative thresholds: values below five produced excessive network fragmentation with numerous isolated low-connectivity nodes, while higher thresholds substantially reduced the number of retained keywords without meaningfully improving cluster coherence. This threshold is also consistent with common practice in bibliometric studies of comparably sized datasets (approximately 100–150 documents). The resulting network was visualized using three complementary map types: network visualization to identify thematic clusters and inter-cluster relationships, overlay visualization to examine the temporal evolution of research topics, and density visualization to detect areas of concentrated intellectual activity. Together, these analytical procedures enabled a structured and replicable mapping of the thematic architecture of AIED research during the study period.

## 3. RESULT

This section reports the principal bibliometric findings derived from the 107 peer-reviewed journal articles retrieved from the Scopus database, covering the period 2021 to 2026. The results are organized around three of the study's research objectives: annual publication trends and subject area distribution address Objective 1 (Sections 3.1–3.2), the keyword co-occurrence network addresses Objective 2 (Sections 3.4–3.5), and the country-level distribution addresses Objective 3 (Section 3.3). Each subsection reports the descriptive patterns observed in the data; the substantive interpretation of these patterns, including their implications for curriculum development and vocational education, is presented in the corresponding subsections of the Discussion.

3.1. Annual Publication Trends in AI in Education Research

The temporal distribution of publications across the study period is presented in Figure 3, based on the final dataset of 107 documents.

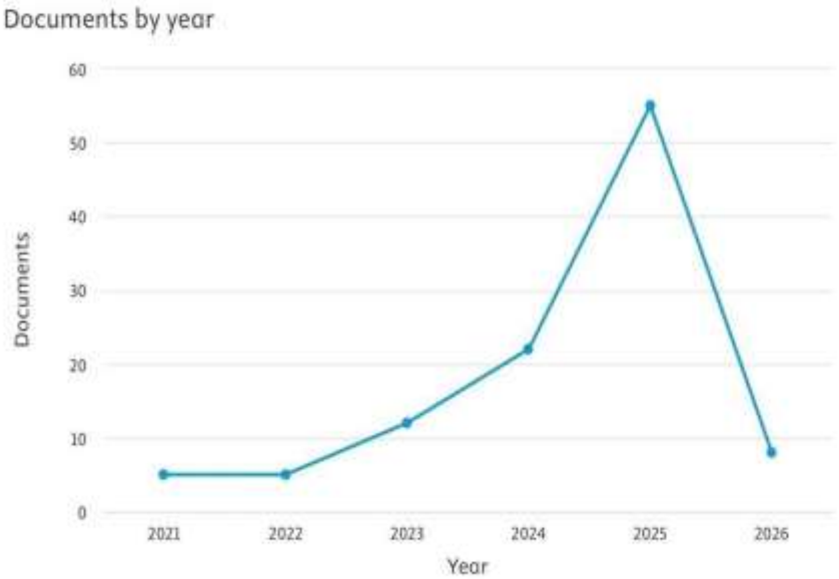


**Figure 3. Annual Publication Trends in AI in Education Research (2021–2026)**
**(Source: Scopus Database, 2026)**

Publication output during the initial two years of the study period remained comparatively low, with five documents recorded in both 2021 and 2022, together accounting for 9.4% of the dataset. The thematic composition of this early period is examined further in the keyword overlay analysis in Section 3.5. Publication volume increased to 12 documents in 2023, 22 in 2024, and 55 in 2025, the highest annual output in the dataset. The 2023–2025 period accounts for 89 of the 107 publications, or 83.2% of the dataset. This acceleration is interpreted in relation to the diffusion of generative AI technologies in Section 4.1.

The 2026 figure shows a reduction to 8 documents. Because bibliographic records were retrieved from Scopus in January 2026, this figure reflects a partial year rather than a complete annual count and is excluded from comparative trend analysis. The annual distribution of publications across the study period is summarized in Table 2.

**Table 2**
**Annual Publication Frequency in AIED Research (2021–2026)**

| Year | Number of Publications | Cumulative Total | % of Dataset |
|---|---|---|---|
| **2021** | 5 | 5 | 4.7% |
| **2022** | 5 | 10 | 4.7% |
| **2023** | 12 | 22 | 11.2% |
| **2024** | 22 | 44 | 20.6% |
| **2025** | 55 | 99 | 51.4% |
| **2026*** | 8 | 107 | 7.5% |
| **Total** | 107 | | 100% |

3.2. Subject Area Distribution of AI in Education Research

The disciplinary distribution of the 107 publications across Scopus subject area categories is presented in Figure 4.

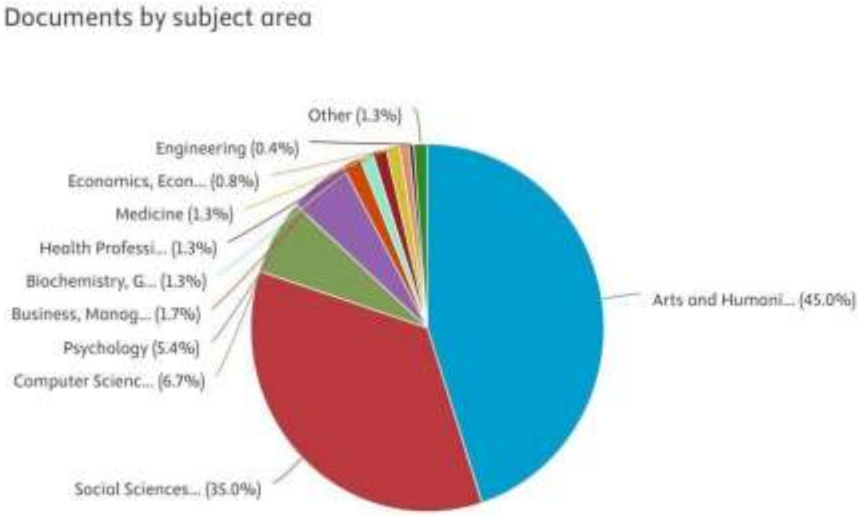


**Figure 4. Subject Area Distribution of AI in Education Research (2021–2026)**
**(Source: Scopus Database, 2026)**

Arts and Humanities accounts for the largest share of the dataset at 45.0%, followed by Social Sciences at 35.0%. Combined, these two categories represent 80.0% of total publications. Social Sciences (35.0%) encompasses studies classified under educational sociology, policy analysis, curriculum theory, and instructional design in the Scopus subject-area taxonomy. Psychology represents the third largest category at 5.4%.

Computer Science accounts for 6.7% of publications, and Business and Management accounts for 1.7%. The interpretation of this disciplinary balance, including its implications for the field's pedagogical versus technical orientation, is presented in Section 4.2. The remaining subject areas each account for 1.3% or below: Biochemistry and related life sciences (1.3%), Health Professions (1.3%), Medicine (1.3%), Economics and Econometrics (0.8%), Engineering (0.4%), and a residual Other category (1.3%).

3.3. Geographical Distribution of Research Productivity

The country-level output for the ten most productive nations is presented in Figure 5.

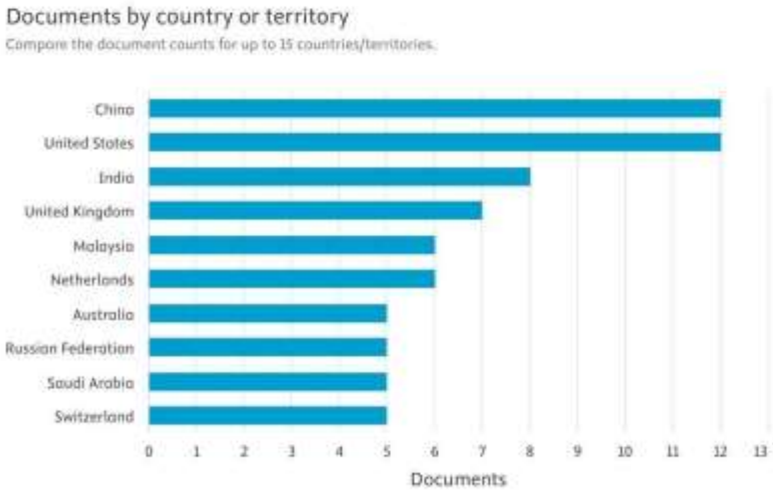


**Figure 5. Distribution of Publications by Country or Territor(2021–2026)**
**(Source: Scopus Database, 2026)**

China and the United States jointly lead global research productivity, each contributing approximately 12 publications and together accounting for 22.4% of the 107 documents. India ranks third with approximately 8 publications, followed by the United Kingdom with 7. Malaysia and the Netherlands each contributed approximately 6 publications.

Australia, the Russian Federation, Saudi Arabia, and Switzerland each produced approximately 5 publications. No country from Sub-Saharan Africa, Latin America, or Southeast Asia beyond Malaysia appears among the ten most productive countries in the dataset. Overall, the top two countries account for 22.4% of the dataset and the top four countries account for approximately 36.4%. The implications of this geographical concentration for the representativeness of AIED knowledge production are discussed in Section 4.3.

3.4. Keyword Co-Occurrence Network Analysis

The keyword co-occurrence network was constructed from the final dataset of 107 publications using VOSviewer version 1.6.21, applying a minimum co-occurrence threshold of five, full counting, and association strength normalization. The resulting network, presented in Figure 6, identifies four distinct thematic clusters, differentiated by color, that directly address Objective 2 of this study.

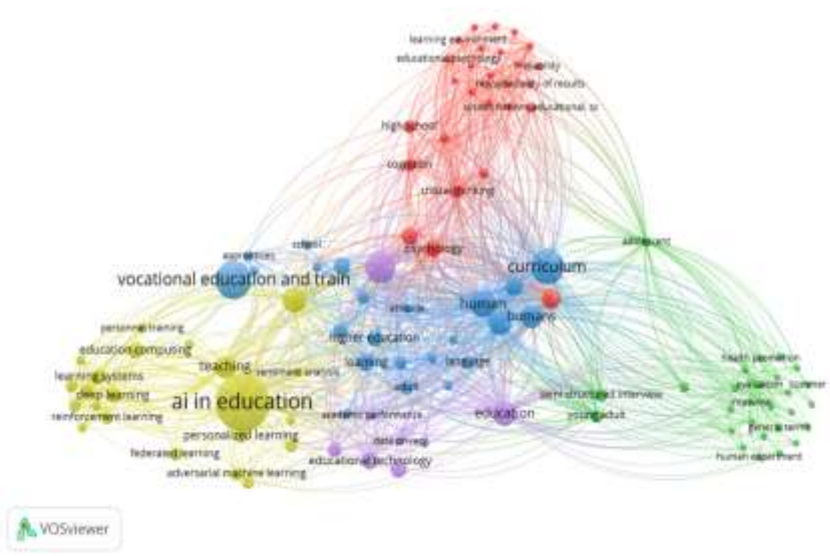


**Figure 6. Network Visualization of Keyword Co-Occurrence in AIED Research (2021–2026) (Source: VOSviewer Analysis, 2026)**

The term education occupies the most central nodal position in the network, indicating that it co-occurs with the widest range of keywords across the dataset. Curriculum, human, ai in education, and teaching also function as high-connectivity nodes linking multiple clusters. The first cluster (yellow-green) is anchored by the terms ai in education, vocational education and training, and teaching, and further includes deep learning, reinforcement learning, federated learning, adversarial machine learning, learning systems, personalized learning, education computing, personnel training, school, and apprentices. This is the cluster in which vocational education and training terms co-occur with technical AI methodology terms; the significance of this co-occurrence for the study's focus on vocational education is discussed in Section 4.4.

The second cluster (red) includes learning environment, educational psychology, cognition, critical thinking, high school, reliability, reproducibility of results, and united nations educational science. The third cluster (blue-purple), the most densely connected in the network, is organized around curriculum, human, humans, psychology, higher education, learning, attitude, language, sentiment analysis, academic performance, data privacy, and educational technology. This cluster occupies the network's geometric center and contains the study's core curriculum-related keyword, curriculum, discussed further in Section 4.4.

The fourth cluster (green) includes adolescent, young adult, adult, semi-structured interview, evaluation, health promotion, human experiment, and general terms. The four clusters correspond to four intersecting research axes: technical AI implementation within vocational contexts, cognitive and psychological learning outcomes, curriculum and pedagogical design within higher education, and demographic-specific evaluative research. The interconnectivity of these clusters is interpreted in Section 4.4.

3.5. Temporal Evolution of Research Themes

The overlay visualization presents the same keyword co-occurrence network as Figure 6, with each node colored according to the average publication year of documents in which the keyword appears. The temporal scale spans from 2024.0 (dark blue-purple) to 2025.0

(bright yellow-green), presented in Figure 7.

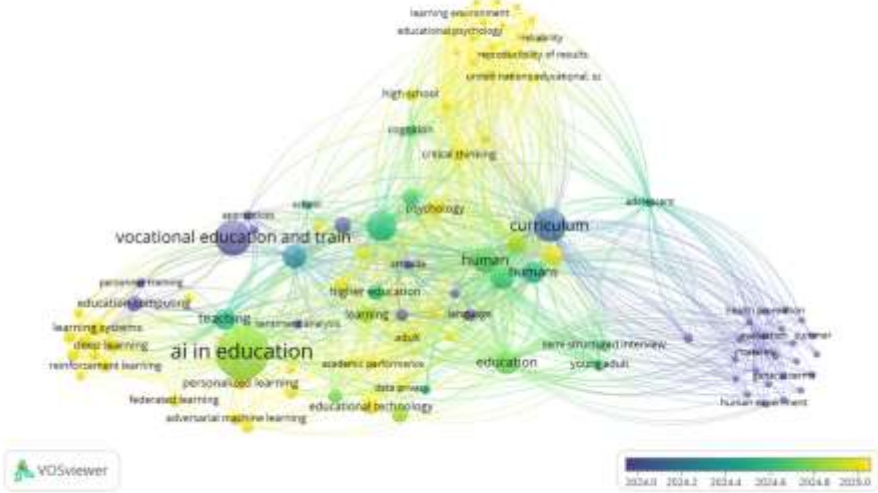


**Figure 7. Overlay Visualization of Keyword Evolution (2021–2026)**
**(Source: VOSviewer Analysis, 2026)**

Keywords with an average publication year closer to early 2024 include vocational education and training, deep learning, reinforcement learning, learning systems, education computing, personnel training, apprentices, high school, united nations educational science, adolescent, semi-structured interview, health promotion, and human experiment. Keywords with an average publication year of approximately mid-2024 include ai in education, teaching, curriculum, human, humans, learning, higher education, psychology, cognition, critical thinking, learning environment, educational technology, personalized learning, and federated learning.

Keywords with an average publication year approaching 2025.0 include academic performance, data privacy, sentiment analysis, attitude, language, reliability, reproducibility of results, educational psychology, adversarial machine learning, young adult, adult, and evaluation. Taken together, the overlay visualization shows a three-phase temporal progression, from an earlier band of vocational and technical AI terms, through a mid-period band of core pedagogical and curricular terms, to a most recent band of data-ethics, methodological, and affective-learning terms. The significance of this progression for the study's curriculum and vocational education focus is discussed in Section 4.5.

3.6. Citation Impact of AIED Research (2021–2026)

To incorporate an additional bibliometric indicator beyond keyword co-occurrence, citation metrics were derived from the same 107-document dataset used for the network analyses in Sections 3.4 and 3.5. Across the dataset, documents received a combined total of 667 citations (M = 6.23, Mdn = 1), yielding a dataset h-index of 11. Fifty-one documents (47.7%) had received no citations at the time of data retrieval. The distribution of citations by publication year is presented in Table 3.

**Table 3**
**Citation Distribution by Publication Year (2021–2026)**

| Year | N Documents | Total Citations | Mean Citations/Document |
|---|---|---|---|
| **2021** | 5 | 22 | 4.40 |

| | | | |
|---|---|---|---|
| **2022** | 5 | 27 | 5.40 |
| **2023** | 12 | 95 | 7.92 |
| **2024** | 22 | 271 | 12.32 |
| **2025** | 55 | 251 | 4.56 |
| **2026** | 8 | 1 | 0.12 |
| **Total** | 107 | 667 | 6.23 |

Because more recently published documents have had less time to accumulate citations, the lower mean citation count observed for 2025 (4.56) relative to 2024 (12.32) reflects this citation-lag effect rather than a decline in scholarly impact; this caveat is addressed further in Section 4.6.

The five most-cited documents in the dataset are presented in Table 4.

**Table 4**
**Five Most-Cited Documents in the AIED Dataset (2021–2026)**

| Rank | Citations | Author(s) | Year | Source Title |
|---|---|---|---|---|
| **1** | 181 | Giannakos et al. | 2025 | Behaviour and Information Technology |
| **2** | 65 | Liu, Hwang, Chen, Chen & Ye | 2024 | Computer Assisted Language Learning |
| **3** | 62 | Yapp, de Graaff & van den Bergh | 2023 | Language Teaching Research |
| **4** | 50 | Vallis, Wilson, Gozman & Buchanan | 2024 | Postdigital Science and Education |
| **5** | 37 | Werdiningsih, Marzuki & Rusdin | 2024 | Cogent Arts and Humanities |

None of the five most-cited documents address vocational education specifically; the highest-cited work concentrates on generative AI applications in general and language education. The implications of this pattern for the study's focus on curriculum development and vocational education are discussed in Section 4.6.

## 4. DISCUSSION

This section interprets the results reported in Sections 3.1–3.6 in relation to the study's three research objectives and the broader AIED literature, with particular attention to the implications for curriculum development and vocational education transformation. Because bibliometric analysis describes publication and co-occurrence patterns rather than causal mechanisms, each interpretation below is presented with the corresponding methodological caveats, and Section 4.7 consolidates the study's principal limitations. Section 4.8 states explicitly how the study's findings extend prior AIED bibliometric reviews, and the section closes with specific directions for future research in Section 4.9.

### 4.1 The Post-2022 Publication Surge: Plausible Drivers and Interpretive Caution

The concentration of 83.2% of publications within 2023–2025 (Section 3.1) indicates a marked temporal inflection in AIED publication counts, but the bibliometric data alone cannot establish what caused it. The timing coincides with the public diffusion of large language models from late 2022 onward, and it is plausible that the resulting accessibility of generative AI tools to educators and learners without specialized technical infrastructure reshaped the field's research agenda (Burton & O'Neal, 2024; Storey & Wagner, 2024). However, at least two alternative or complementary explanations cannot be ruled out by publication-count data alone. First, Scopus's own journal coverage expanded over this period, and an unknown share of the observed increase may reflect newly indexed venues rather than genuine growth in scholarly output. Second, global research funding priorities and university publication incentives shifted toward AI-related topics across many fields during this period, independent of any specific technological trigger, which could inflate AIED counts through general publication incentives rather than substantive engagement with generative AI specifically. The acceleration reported here is therefore best read as a publication-pattern finding consistent with, but not proof of, a generative-AI-driven inflection.

With this caveat in place, the pattern still aligns with Prasetya et al. (2025), who identified a comparable acceleration in VET-focused AI research following the same period. Read together, the two studies suggest that whatever combination of factors drove the increase, it was not confined to general AIED scholarship but extended into vocational-specific research as well. For curriculum developers, the practical implication is double-edged: a substantially larger evidence base now exists to inform AI-integrated vocational curriculum design than existed before 2023, but because this evidence base is so recently produced, much of it has not yet been tested through replication, longitudinal evaluation, or independent citation scrutiny (see Section 4.6). Curriculum reform drawing on this literature should therefore treat very recent findings as provisional rather than established.

### 4.2. Disciplinary Orientation: A Pedagogical Turn, or an Artifact of Classification and Search Strategy

The concentration of publications in Arts and Humanities (45.0%) and Social Sciences (35.0%), against a modest 6.7% for Computer Science (Section 3.2), invites a straightforward reading: that AIED scholarship is led by humanistic and social-scientific traditions rather than technical ones. This reading is consistent with Lampropoulos et al. (2022), who argue that technology integration in education requires engagement with learning theory and institutional context rather than technical metrics alone. However, two sources of bias temper how far this claim can be generalized. First, Scopus's ASJC subject classification is assigned at the journal or source level in many cases, meaning an article's disciplinary label may reflect where its host journal is classified rather than the article's actual methodological orientation; a computationally oriented AIED study published in an education journal would likely be coded as Social Sciences regardless of its technical content. Second, the search strategy itself, requiring both “Artificial Intelligence” and “Education” in the title, abstract, or keywords, may systematically underrepresent technical AI research that describes its educational application only briefly, while more fully capturing education-oriented research that foregrounds pedagogical framing in its abstract by design. The observed disciplinary distribution should therefore be read as a property of the literature captured by this search strategy and Scopus's classification system, not as direct evidence of where AIED research as a whole is intellectually centered.

Taken with this caveat, the finding still carries a practical implication worth stating plainly for curriculum developers: research written for a technical audience is less likely to appear when educators search Scopus using education-centered terms, and vocational curriculum teams relying on searches similar to this study's should expect to supplement their evidence base with computer-science-indexed literature located through different search strategies if they need implementation-level technical detail alongside pedagogical guidance.

### 4.3. Geographical Concentration: Global Knowledge Gap or Database Visibility Gap

The concentration of output in China, the United States, India, and the United Kingdom (Section 3.3) is consistent with those countries' broader AI research investment and policy commitments (Zhang et al., 2025; Ghosh & Ravichandran, 2024). Read at face value, the near-absence of Sub-Saharan Africa, Latin America, and most of Southeast Asia beyond Malaysia would suggest that AIED knowledge production is genuinely concentrated in a small number of high-income nations. A more cautious reading is warranted, however, because Scopus systematically indexes a smaller proportion of journals published in, or oriented toward, the Global South than journals from North America, Western Europe, and East Asia. The absence of a country from this dataset's top ten is therefore consistent with two different underlying realities that this analysis cannot distinguish: genuinely limited AIED research activity in that region, or research activity published in venues Scopus does not index. This distinction matters directly for vocational education research, since VET systems are inherently shaped by local labor-market structures and apprenticeship traditions that vary by region (Long, 2023; Karwa, 2025); if regional AIED-VET scholarship exists primarily in non-Scopus-indexed venues, this study's dataset would understate rather than accurately represent the field's engagement with vocational contexts outside the dominant research economies. Either interpretation supports the same practical conclusion: deliberate investment in research capacity and indexed-journal access in underrepresented regions, including Indonesia and broader Southeast Asia, would meaningfully improve the field's ability to produce vocational AI curricula that are locally valid rather than imported wholesale from high-income research contexts.

### 4.4. Thematic Architecture: What Curriculum Centrality Does, and Does Not, Establish

The centrality of curriculum as a high-connectivity node, and the co-anchoring of vocational education and training within the same cluster as deep learning, reinforcement learning, and federated learning (Section 3.4), is the study's most direct evidence that AI-vocational integration is an established rather than emergent research domain (Prasetya et al., 2025; Ghosh & Ravichandran, 2024). This finding should nonetheless be interpreted within the bounds of what keyword co-occurrence can show. Co-occurrence reflects which author-supplied keywords appear together in the same documents; it indicates topical proximity, not conceptual depth, methodological rigor, or practical implementation readiness. A cluster in which vocational education and training co-occurs with deep learning does not establish that any given study in that cluster provides an actionable curriculum design, only that the two concerns are discussed within the same body of literature. With that qualification, the finding still extends Wang and Jia's (2023) argument that curriculum reform under AI adoption requires rethinking how competencies are sequenced and assessed, since the network structure indicates the scholarly community is already discussing AI methodology and vocational competency development in the same conversational space, a necessary but not sufficient condition for the kind of integrated curriculum reform Wang and Jia call for. Unlike Prasetya et al. (2025), which examined VET-AI research on its own terms, this is, to our knowledge, the first study to position vocational education structurally within the broader AIED keyword network, showing where it sits relative to personalized learning, curriculum, and higher-education-oriented clusters rather than treating it as a self-contained literature.

For curriculum developers, the practical implication is that the building blocks for AI-integrated VET curricula, personalized learning approaches, adaptive assessment models, and technical AI methods, already exist in the literature and are discoverable through the same search space as general AIED scholarship. What remains underdeveloped, based on the citation patterns reported in Section 4.6, is translation of this thematic proximity into widely recognized, highly cited exemplars that vocational institutions can adopt with confidence.

4.5. Temporal Evolution: A Short Window, Read Cautiously

The overlay analysis (Section 3.5) shows keywords distributed across an average-publication-year range of only 2024.0 to 2025.0, a span of approximately twelve months. This compression itself is an important interpretive constraint: because 55 of the 107 documents, over half the dataset, were published in 2025 alone, keywords that happen to co-occur more frequently with 2025 publications will mechanically show a later average publication year regardless of whether they represent a genuinely emergent research concern or simply reflect the dataset's heavy skew toward 2025. The apparent “late-phase” emergence of data privacy, adversarial machine learning, reliability, and reproducibility of results should therefore be treated as a tentative signal rather than a confirmed three-phase maturation trajectory; distinguishing genuine thematic emergence from a volume-driven artifact would require a within-2025 breakdown or a follow-up analysis once 2026 data are complete, neither of which the current dataset supports.

With that caution stated, the earlier consolidation of vocational education and training alongside deep learning and learning systems remains a comparatively more stable observation, since it draws on keywords distributed across the full 2021–2026 window rather than concentrated in the final year, and is consistent with the longer developmental history of intelligent tutoring systems in vocational and professional training contexts (Haji & Azmani, 2020). For VET researchers, this suggests that the technical foundation for AI-supported vocational training is comparatively well established, while the field's more recent attention to data privacy, algorithmic governance, and empirical reproducibility, if genuine rather than volume-driven, represents the next area vocational AI curriculum research would need to address before institutional adoption at scale.

4.6. Citation Impact: Structural Presence Without Citation Visibility

The citation analysis reported in Section 3.6 adds a dimension the keyword network cannot: evidence of which AIED research has accumulated scholarly recognition, as distinct from which research exists. The finding that none of the five most-cited documents in the dataset addresses vocational education specifically, with the highest-cited work instead concentrated on generative AI in general and language education, is a meaningful complement to the Cluster 1 finding in Section 4.4. Vocational education and training co-occurs with technical AI terms in the keyword network, indicating topical proximity, but this proximity has not yet translated into the field's most visible or heavily cited work. Two caveats limit how far this should be pushed. First, citation counts are strongly time-dependent, and the dataset's heavy skew toward 2024–2025 publications means most documents, vocational or otherwise, have had limited time to accumulate citations; the citation gap observed here may narrow as the literature matures rather than reflecting a permanent structural neglect of vocational applications. Second, citation counts reward broad audience relevance as much as research quality, and topics such as ChatGPT and generative AI in general education attract wider readership than specialized vocational applications independent of their comparative scholarly rigor. Taken together, the citation pattern is best read as converging evidence, alongside the geographical and disciplinary findings in Sections 4.2 and 4.3, that vocational-specific AIED research remains structurally present but comparatively under-recognized, reinforcing rather than independently proving the study's central novelty claim.

4.7. Methodological Limitations

Several limitations bound the interpretations offered above and should be considered jointly rather than as isolated caveats attached to individual findings. First, reliance on a single database, Scopus, means the dataset reflects Scopus's indexing policies and coverage biases rather than the full universe of AIED publications; Web of Science and Dimensions index partially non-overlapping journal sets, and cross-database replication was outside this study's scope. Second, the two-term Boolean search strategy, while validated against an expanded-term comparison search during data collection, necessarily privileges documents that explicitly frame their contribution using the words “artificial intelligence” and “education” together, which may underrepresent technically framed or regionally published work using different terminology. Third, keyword co-occurrence analysis operates on author-supplied keywords rather than full-text content, meaning thematic clusters reflect labeling conventions as much as substantive content, a limitation particularly relevant to the disciplinary classification discussed in Section 4.2. Fourth, the study's temporal window, while deliberately bounded to capture the post-2021 generative AI period, produces an overlay analysis compressed into a twelve-month average-year range, limiting confidence in any claimed multi-phase temporal progression, as discussed in Section 4.5. Finally, as with all bibliometric research, the findings describe patterns of publication, co-occurrence, and citation; they do not establish causal mechanisms, and claims throughout this Discussion have been framed as consistent with, rather than proof of, the interpretations offered.

### 4.8. Novelty and Contribution Relative to Prior AIED Bibliometric Reviews

Three features distinguish this study from the existing bibliometric literature on AI in education. First, unlike broader AIED bibliometric reviews spanning longer or earlier historical windows, this study is deliberately bounded to 2021–2026, isolating the post-generative-AI period specifically rather than diluting it within a longer time series. Second, and most substantively, this is, to our knowledge, the first study to position vocational education and training structurally within the broader AIED keyword co-occurrence network rather than examining VET-AI research in isolation, as in Prasetya et al. (2025), or omitting vocational education as a distinct analytical category altogether, as in general AIED bibliometric reviews. This structural positioning, showing where VET sits relative to personalized learning, curriculum, and higher-education clusters, is the study's central empirical contribution. Third, the addition of citation-based analysis alongside keyword co-occurrence, reported in Section 3.6 and interpreted in Section 4.6, provides a reach-and-recognition dimension that prior VET-AI bibliometric work has not incorporated, revealing a gap between vocational education's topical presence and its citation visibility that keyword mapping alone would not have surfaced.

### 4.9. Directions for Future Research

Building on the knowledge gaps and limitations identified above, four directions appear most warranted. First, given the geographical concentration reported in Section 4.3 and its particular relevance to VET systems, future bibliometric and empirical research should specifically target AI integration in curriculum development and vocational education within developing countries and Global South contexts, potentially drawing on regionally indexed databases alongside Scopus to counteract the coverage bias discussed in Section 4.7. Second, replication of this analysis using Web of Science or Dimensions, or a multi-database triangulation design, would help determine how much of the disciplinary and geographical distribution reported here reflects genuine field structure rather than Scopus-specific indexing patterns. Third, given the temporal compression noted in Section 4.5, a longitudinal follow-up analysis once 2026 and subsequent years of data are fully indexed would allow the tentative three-phase progression proposed here to be tested against a less recency-skewed dataset. Fourth, the citation-visibility gap identified in Section 4.6 suggests a need for future research that explicitly evaluates the practical implementation outcomes of AI-integrated vocational curricula, rather than their bibliometric presence alone, potentially through mixed-methods designs pairing bibliometric mapping with case studies of vocational institutions that have adopted AI-supported training models.

## 5. CONCLUSION

This study mapped the intellectual structure and thematic development of Artificial Intelligence in Education (AIED) research published between 2021 and 2026, with particular attention to how curriculum development and vocational education are positioned within this literature. The three research objectives, growth trajectory and disciplinary distribution, thematic cluster structure, and geographical distribution, were addressed through bibliometric analysis of 107 peer-reviewed journal articles, extended by a citation analysis not originally planned in the study design but incorporated to provide a reach-and-recognition dimension alongside the keyword network.

The study's principal contribution is not the confirmation that AIED publication activity has grown since 2023, which is a descriptive pattern consistent with, though not proof of, the broader diffusion of generative AI, but the structural positioning of vocational education and training within the wider AIED knowledge network. Unlike prior bibliometric reviews that examine VET-AI research in isolation or omit vocational education as a distinct category altogether, this study shows specifically where vocational themes sit relative to personalized learning, curriculum, and higher-education-oriented clusters, and further shows, through citation analysis, that this topical presence has not yet translated into the field's most-cited or most visible work. Read together, these two findings offer a more precise account of vocational education's place in AIED scholarship than publication counts or thematic clustering could establish alone.

For curriculum developers and VET policymakers, these findings suggest that a growing evidence base for AI-informed vocational curriculum design now exists and is discoverable within mainstream AIED literature, though this evidence base remains recent and largely untested through replication or independent citation scrutiny, and should be treated accordingly rather than as settled practice. The geographical concentration of research output in a small number of high-income nations further suggests that frameworks drawn from this literature may require deliberate contextual adaptation before application in Southeast Asian or other underrepresented vocational education systems, rather than direct adoption.

These conclusions should be read alongside the study's limitations, discussed in full in Section 4.7: reliance on a single database (Scopus), a search strategy bounded to two core terms, and a 2021–2026 window that compresses the temporal overlay analysis into a twelve-month average-year range. Each of these choices shaped what the dataset could and could not reveal, and the findings are best understood as characteristic of the literature this specific search strategy retrieved rather than as a complete account of the AIED field.

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