



A Bounded Bibliometric Profile of Artificial Intelligence Education Research

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Abstract

Bibliometric profiles based on relevance-ranked searches may conflate patterns of research publication with patterns of record retrieval. This study examined the descriptive characteristics and interpretive limits of a bounded Crossref corpus on artificial intelligence in education. On 17 September 2026, the first 100 records returned for the query artificial intelligence education, restricted to journal articles published during 2016–2025, were obtained. Records were assessed in retrieval order, and the first 30 with an author field and the complete phrase artificial intelligence in their titles, excluding editorial or corrective items, formed the analytical corpus. Publication year, journal, authorship, Crossref citation counts, and seven non-exclusive title dictionaries were analysed descriptively. Twenty-six records (86.7%) were published in Computers and Education: Artificial Intelligence and four (13.3%) in the International Journal of Artificial Intelligence in Education; 25 appeared during 2022–2025. School-related terms occurred in eight titles, teacher-related terms in five, and ethics-related terms in two. Median authorship was two, and the median recorded citation count was 100. These distributions reflect a fixed search and stopping rule, not population-wide publication frequencies. The study demonstrates how transparent metadata analysis can identify observable patterns while exposing the inferential constraints introduced by search formulation, ranked retrieval, and restrictive eligibility criteria.

Keywords: artificial intelligence, bibliometrics, Crossref, educational research, metadata.



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INTRODUCTION

Artificial intelligence (AI) research in education encompasses intelligent learning systems, curriculum development, instructional practices, teacher preparedness, and the institutional implications of educational technologies. The development of this research area reflects changes in technological capabilities and educational priorities, making its scholarly characteristics difficult to represent through a single application or research category. Historical and conceptual studies have examined the evolution of AI in education, its underlying paradigms, and the relationship between technological innovation and educational theory (Doroudi, 2023; Ouyang & Jiao, 2021; Roll & Wylie, 2016). Bibliometric analysis offers a means of describing publication characteristics through structured metadata. However, the validity of its interpretations depends on database coverage, retrieval procedures, sampling decisions, and the indicators used to represent scholarly activity. These methodological conditions become particularly consequential when a limited set of retrieved publications is used to describe a rapidly developing research area.

Previous literature reviews have examined AI applications across educational settings and research domains. Su and Yang (2022) investigated AI in early childhood education through a scoping review, while Su and Zhong (2022) and Yang (2022) addressed curriculum development and instructional considerations for young learners. Martin et al. (2024) systematically reviewed AI research in K–12 education, whereas Laupichler et al. (2022)

examined AI literacy in higher and adult education. These studies provide evidence about particular educational populations, applications, and research concerns. Their substantive objectives differ from an examination of how bibliographic retrieval procedures determine the composition of an analytical dataset. Although systematic reviews and bibliometric investigations can identify publication characteristics and research concentrations, their findings do not independently establish whether observed distributions reflect the underlying literature or the selection mechanisms through which records were obtained.

A methodological problem arises when search-derived publication distributions are interpreted without adequate consideration of retrieval conditions. Bibliometric indicators describe records included in an analytical corpus, but database indexing, search terminology, relevance ranking, and eligibility restrictions can systematically influence which publications become visible. This distinction is especially important when search expressions overlap with journal titles or other bibliographic fields. A concentration of records within particular journals may reflect substantive publication patterns, retrieval preferences, or interactions between both factors. Existing conceptual and review literature establishes the diversity of AI education research, but it does not resolve how a fixed, relevance-ranked Crossref search shapes the publication profile generated from a restricted metadata sample. The specific gap addressed here concerns the transparency and interpretive limits of query-conditioned bibliometric description rather than the comprehensive mapping of AI education scholarship.

Crossref was selected as the bibliographic source because its publicly accessible REST API provides structured, DOI-linked publication metadata that can be retrieved and examined through a specified request (Crossref, 2026). These records support the description of publication years, journal outlets, authorship counts, citation metadata, and article titles without requiring institutional access to subscription-based bibliometric databases. Nevertheless, Crossref primarily operates as a scholarly metadata registration infrastructure and differs from curated citation databases such as Scopus and Web of Science in coverage, metadata completeness, and citation indexing. Its citation counts are influenced by deposited reference information, publication age, and differences in record coverage. Consequently, recorded citations indicate source-specific scholarly visibility rather than research quality or educational effectiveness (Chen et al., 2020; Roll & Wylie, 2016). The present investigation uses Crossref for a reproducible metadata-based demonstration, not as a comprehensive substitute for established bibliometric databases.

The analytical scope also requires a distinction between bibliometric description and substantive content analysis. Publication year, journal distribution, listed author counts, and recorded citations constitute bibliographic indicators, whereas title-based lexical classification identifies explicitly stated research objects. Article titles can disclose educational settings, technologies, and professional concerns, but they cannot establish the complete thematic content or empirical findings of individual publications. Studies addressing teacher acceptance, institutional barriers, ethical principles, and educational rights demonstrate the variety of concerns represented in AI education scholarship (Adams et al., 2023; Al Darayseh, 2023; Persson, 2024; Wang & Cheng, 2021). A predefined lexical dictionary allows these expressions to be counted consistently while preserving the distinction between observable terminology and substantive research content. The resulting procedure is a descriptive bibliometric profile incorporating title-level lexical coding, rather than a full-text systematic review, thematic synthesis, or inferential assessment of research trends.

This study examines thirty eligible journal-article records selected in returned order from the first 100 relevance-ranked Crossref records retrieved using the query *artificial intelligence education* and a publication-date filter covering 2016–2025. The restricted corpus serves a methodological purpose: to establish which descriptive indicators can be reproduced from a defined retrieval procedure and how their interpretation is constrained by the selection rules.

Three research questions guide the investigation: (1) What publication-year, journal, authorship, and citation patterns are observable within the bounded Crossref sample? (2) Which educational settings, technological categories, and professional or ethical concerns are explicitly represented in the selected article titles? (3) How do the search formulation, relevance-ranked retrieval, and operational eligibility criteria condition the resulting publication profile and its interpretation? The study contributes an inspectable relationship between bibliographic selection procedures, metadata distributions, and the limits of bibliometric inference. Its findings concern retrieval visibility within a defined Crossref dataset and do not establish field-wide publication prevalence, longitudinal growth, or the substantive effectiveness of AI applications in education.

RESEARCH METHODS

This study employed a descriptive bibliometric design incorporating structured metadata analysis and title-level lexical classification. Bibliographic records were retrieved from the Crossref REST API on 17 September 2026 using the search expression *artificial intelligence education*, with the document type restricted to *journal-article* and publication dates limited to 1 January 2016–31 December 2025. The retrieval comprised the first 100 records returned in the API's relevance-ranked order within a single response. Records were analysed according to their original retrieval positions, without subsequent ranking by citation frequency, publication year, or journal. Crossref was selected because its publicly accessible DOI-linked metadata permit an inspectable examination of how search and selection procedures influence descriptive publication profiles. As a publisher-deposited metadata infrastructure, Crossref differs from curated bibliometric databases in disciplinary coverage, reference completeness, and citation indexing. The analysis consequently concerns the visibility of publications within a specified Crossref retrieval procedure rather than comprehensive coverage of artificial intelligence education research (Crossref, 2026).

The sampling procedure applied predefined eligibility conditions to the retrieved records in their returned order. Eligible records were required to contain an author field and the complete expression *artificial intelligence* in the decoded article title. Records containing the terms *erratum*, *correction*, *commentary*, or *editor* in their titles were excluded. The first 30 records satisfying these conditions constituted the final analytical corpus. The remaining 70 retrieved records were not included in the analysis, although this difference should not be interpreted as 70 individually rejected publications because the selection procedure employed a fixed stopping rule. The restriction to 30 records was an operational boundary established for methodological demonstration and did not represent a statistical sample-size calculation, evidence of thematic saturation, or a claim of bibliographic completeness. The complete-phrase requirement also excluded otherwise relevant titles using only abbreviations such as *AI* or alternative terminology. These restrictions were treated as characteristics of the selection mechanism rather than indicators of the substantive boundaries of the research field.

The retrieval and selection procedure was documented through the original API request, archived response, selection code, and extracted metadata. The single-response retrieval avoided multi-page result aggregation, while the archived record sequence preserved the ranking observed on the retrieval date. This distinction was necessary because relevance-ranked results may change as publisher metadata, indexed records, and search conditions evolve. The screening sequence distinguished the initial retrieval of 100 records from the retention of 30 eligible publications, without interpreting records outside the final corpus as substantive negative screening outcomes. DOI identifiers provided the bibliographic reference for selected publications; the 30 retained records had distinct DOI identifiers. The complete selected-record metadata and corresponding bibliographic references provided an auditable basis for the subsequent calculations.

For each selected record, the extracted variables comprised DOI, decoded article title, publication year, journal title, number of listed authors, Crossref *is-referenced-by-count*, and *reference-count*. Publication years were assigned using the deposited publication dates. Journal distributions were calculated as the proportion of the 30 selected records associated with each outlet, while annual frequencies described the publication dates represented within the same corpus. Authorship was measured as the number of contributors listed for each record without individual author disambiguation or institutional affiliation analysis. Citation visibility was described using the Crossref citation count available at retrieval, with the median used to summarise the distribution. Citation counts were not normalised by publication age or disciplinary category and were not interpreted as measures of research quality, conceptual influence, or educational effectiveness. Geographic collaboration patterns were excluded because the available metadata did not establish consistently comparable institutional or national affiliations.

Title-level lexical classification used seven predefined, non-exclusive dictionaries applied to lowercased article titles. The categories and their matching expressions were: early childhood (*early childhood, young children*); school education (*K-12, school, elementary, primary, secondary*); higher education (*higher, university, postgraduate, adult*); teachers (*teacher, instructor*); ethics and rights (*ethic, rights, equity*); literacy (*literacy*); and generative artificial intelligence (*generative*). Each title was assigned a binary match within each category when at least one specified expression was present. Multiple category assignments were permitted, and frequencies were calculated against the common denominator of 30 records. These indicators measured the explicit occurrence of selected terminology rather than the complete thematic content of the publications. A non-matching title was therefore not classified as substantively unrelated to the corresponding topic.

The analytical procedure consisted of descriptive frequency tabulation, proportional distributions, median calculations, and comparisons between metadata categories. Journal concentration, annual publication distribution, title-dictionary frequencies, authorship counts, and citation visibility were examined separately before their methodological implications were assessed. Interpretation distinguished directly observed distributions from possible effects of search formulation, relevance ranking, and eligibility restrictions. The overlap between the search expression and specialised journal titles was treated as a potential source of retrieval concentration, not as an experimentally established ranking effect. No alternative-query experiment, full-text thematic coding, citation-network analysis, inferential statistical testing, or field-wide publication-growth estimation formed part of the analytical design. These boundaries preserved the distinction between reproducible observations within the selected Crossref records and conclusions that would require a broader, independently constructed bibliographic corpus.

RESULTS AND DISCUSSION

Publication Concentration And The Consequences Of Query Design

The thirty selected records were distributed across only two journals. Computers and Education: Artificial Intelligence supplied 26 records, while the International Journal of Artificial Intelligence in Education supplied four. This concentration is the strongest structural feature of the sample, but it should not be interpreted as a market share of all educational artificial intelligence research. Table 1 reports the distribution. Because the query overlaps the titles of these journals, retrieval relevance offers a plausible explanation for the observed concentration.

Table 1. Journal Distribution in the Bounded Sample

Journal	Records	Share (%)
Computers and Education: Artificial Intelligence	26	86.7
International Journal of Artificial Intelligence in Education	4	13.3

Note. The result is query-conditioned and is not a field-wide journal market share.

The publication years ranged from 2016 to 2025, but the range alone conceals the imbalance within that interval. Twenty-five of the thirty records appeared during 2022–2025. Figure 1 shows the yearly counts and preserves years with few observations. This describes the selected records, not a verified acceleration in the entire literature. A historical growth claim would require exhaustive or otherwise comparable annual retrieval rather than the first thirty records produced by a relevance-ranked query.

Two records dated from 2016, and their titles represented broad historical or organisational perspectives. Their inclusion shows that the sample was not restricted to recent generative applications even though recent records predominated. They also illustrate how a topic query can retain older conceptual publications that remain textually relevant. The selection process does not establish whether those publications were foundational to every later study. It establishes their presence and bibliographic characteristics in the archived result (Roll & Wylie, 2016; Timms, 2016).

The 2020 record explicitly joined application and theory gaps in its title. Its presence offers a useful reminder that technical applications and educational explanation are not identical research objects. At the metadata level, the title demonstrates an articulated concern with their relationship. It does not permit the present study to reproduce the article's substantive conclusions without a full-text analysis. This distinction separates bibliometric observation from the literature synthesis that readers might otherwise infer (Chen et al., 2020).

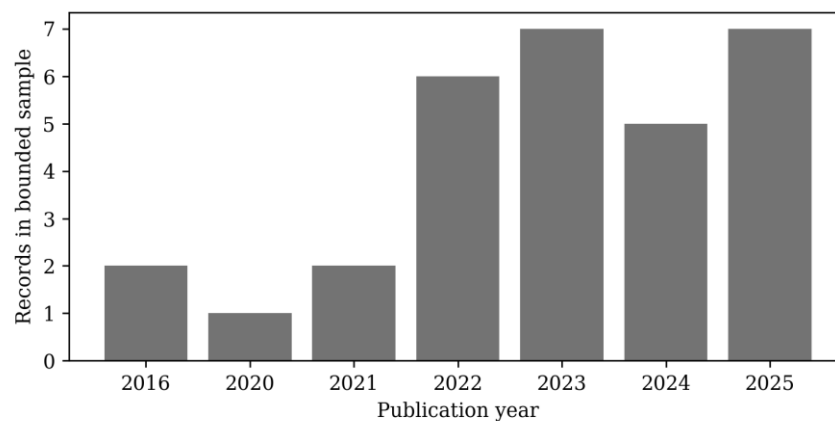


Figure 1. Publication Years in the Bounded Sample

Seven selected records were dated 2023 and seven 2025, compared with six in 2022 and five in 2024. These counts cannot be converted into annual field-wide growth rates because the selection probability of a record is unknown. Differences may reflect query matching, outlet coverage, deposit practices, and the stopping rule as well as publication activity. A more comprehensive bibliometric study would need a stable search universe and explicit handling of online-first and issue publication dates.

The school-focused records illustrate the breadth that can remain inside a concentrated outlet sample. Their titles include systematic reviews of K-12 research and elementary education, alongside work on artificial intelligence literacy in schools. These observations

establish that several educational levels and review forms are visible. They do not show how many studies outside these outlets addressed the same questions. The concentration of journals and diversity of title objects should therefore be reported together (Boulhrir & Hamash, 2025; Martin et al., 2024; Park, 2025).

Some records concerned specific domains such as computer programming, language teaching, and computer vision education. Their coexistence within the sample indicates that artificial intelligence education is not represented solely through general policy or generic learning-system titles. Nevertheless, a domain label does not reveal the quality of the intervention, the characteristics of participants, or the strength of evidence. The present profile treats these titles as research descriptors, not as proof of effectiveness in the named domains (Abichandani et al., 2023; Manorat et al., 2025; Torres & Kahveci, 2025).

The recent publication cluster also included a title linking sustainable education and higher education. This broadens the sample's declared objects beyond immediate classroom performance, but one record cannot establish a wider trend toward sustainability. Small bibliometric samples are especially vulnerable to turning isolated titles into narratives of field transformation. The appropriate interpretation is narrower: the selected corpus contains this topic, and a more extensive search could investigate its prevalence and relationship to other research concerns (Bagherimajd & khajedad, 2025).

The outlet and year distributions demonstrate the value of retaining the entire retrieval procedure. Without the original response and selection rule, the same table could be mistaken for a comprehensive map. With those materials, readers can inspect why particular records entered the sample and rerun alternative rules. The bounded design supports descriptive transparency at the cost of representativeness. That trade-off is an explicit property of this study rather than an unacknowledged limitation of its conclusions.

Educational Settings And Professional Concerns In Title Vocabulary

School-related terms appeared in eight titles, or 26.7% of the selected records. Early-childhood terms appeared in four titles, or 13.3%. These categories overlap conceptually but were counted using separate lexical rules. The resulting frequencies identify explicit educational-level labels rather than all papers relevant to school education. Table 2 reports the dictionaries and counts, and Figure 2 compares their observed frequencies. Articles may address a setting without naming it in the title.

Table 2. Explicit Title Vocabulary

Dictionary category	Matching titles	Share (%)
early childhood	4	13.3
school	8	26.7
higher education	3	10.0
teachers	5	16.7
ethics	2	6.7
literacy	4	13.3
generative AI	4	13.3

Note. Categories overlap. Zero matches would not establish semantic absence.

The early-childhood titles included curriculum design, young children's education, a scoping review, and literacy challenges and opportunities. The variety of descriptors suggests multiple entry points into the same educational stage within the selected records. It does not identify a consensus about instructional practice or a common outcome measure. The present analysis can establish the coexistence of these declared emphases while leaving their

substantive compatibility for a full-text review (Su & Yang, 2022; Su & Zhong, 2022; Su et al., 2023; Yang, 2022).

Higher-education-related expressions appeared in three titles. This should not be read as evidence that higher education is less researched than school education across the field. The matching rule includes only explicit expressions, and some titles may use terms outside the dictionary. A scoping review of higher and adult education and a case study involving university language instructors are examples of records that make the setting visible. They demonstrate coverage within the sample rather than its external completeness (Kohnke et al., 2023; Laupichler et al., 2022).

Teacher-related terms appeared in five titles. The corresponding studies declared interests in acceptance, barriers, preparedness, professional change, and career choice. This distribution indicates that the sampled literature included human and organisational questions alongside technologies. It does not establish that the papers use comparable measures of teacher readiness or that their findings agree. A title-level mapping should preserve these distinctions instead of treating every teacher reference as evidence for a single professional-development model (Al Darayseh, 2023; Cheah et al., 2025; Cheng & Wang, 2023; Martínez-Moreno & Petko, 2024).

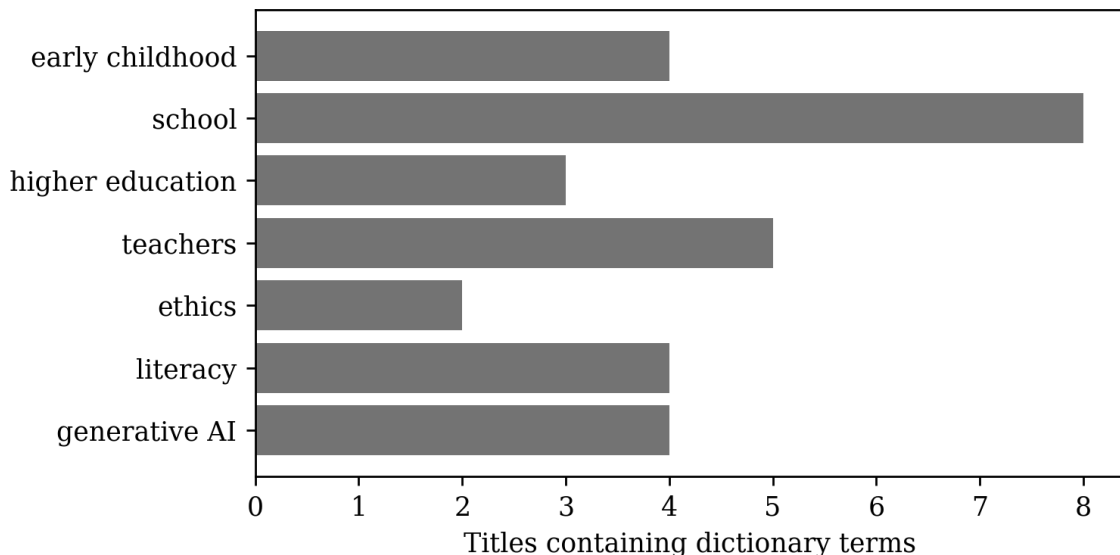


Figure 2. Dictionary Matches in Article Titles

Ethics-, rights-, or equity-related terms appeared in two titles. The small lexical count is a finding about explicit title vocabulary, not a finding that only two articles considered ethics. Ethical analysis may be located in an abstract, methods section, or discussion without being named in the title. The two visible records addressed ethical principles and the redistribution of authority and rights. Their presence establishes a governance concern but cannot measure the depth of ethical treatment across the corpus (Adams et al., 2023; Persson, 2024).

Literacy appeared in four titles, connecting early childhood, schools, primary education, and higher or adult education. The spread across educational stages suggests that literacy is used as a flexible organising concept in the selected records. Its meaning cannot be assumed identical across those settings. A title dictionary recognises the shared term while leaving its operational definitions unresolved. Comparative conceptual work would need to examine what knowledge, practices, and responsibilities each publication includes under literacy (Laupichler et al., 2022; Park, 2025; Su et al., 2023; Yue Yim, 2024).

Generative appeared in four titles and referred to different educational objects. The sampled titles concerned literacy, teacher preparedness, assessment, and university language instruction rather than one uniform application. This pattern cautions against using the presence of generative terminology as a complete thematic classification. The adjective identifies a technological family, while the educational object determines the research question. The present coding records that intersection without claiming that the underlying studies share methods or outcomes (Awidi, 2024; Cheah et al., 2025; Kohnke et al., 2023; Park, 2025).

Several titles resist reduction to the seven dictionaries. Learner competencies, student homework practices, and personalised education can be relevant to educational agency even when the term agency is absent. Their omission from a particular category would reflect the chosen dictionary rather than an absence of substantive significance. This is why the complete metadata table accompanies the summary frequencies. Readers can inspect uncounted vocabulary and assess alternative coding rules without relying on the researcher's thematic labels (Bhutoria, 2022; Sanusi et al., 2022; Turós et al., 2025).

The lexical profile shows that transparent coding makes both findings and omissions visible. School and teacher expressions were relatively frequent within the selected records, while explicit governance vocabulary was less frequent. The result should guide questions for deeper reading rather than rank topics by importance. A subsequent full-text study could compare title emphasis with abstract and discussion content, assess dictionary sensitivity, and identify whether explicit educational-level labels correspond to differences in evidence design.

Authorship Citation Visibility And Limits Of Bibliometric Inference

The median number of listed authors was two. This is a simple description of collaboration as recorded in the metadata, not a measure of interdisciplinary integration or institutional diversity. Two authors may belong to one institution or work across several countries, while a larger team may remain within one discipline. Because affiliations were not disambiguated, the analysis does not report international collaboration rates. Table 3 presents selected citation records alongside the source-specific interpretation required for those counts.

Table 3. Most Cited Records in the Selected Sample

Article title	Year	Crossref citations
Evolution and Revolution in Artificial Intelligence in Education	2016	965
Artificial intelligence in education	2021	698
Application and theory gaps during the rise of Artificial Intelligence	2020	689
Personalized education and Artificial Intelligence in the United State	2022	497
Artificial intelligence literacy in higher and adult education	2022	494

Note. First column identifies the article by shortened title. Counts were retrieved on 17 September 2026 and are not quality scores.

The median Crossref citation count was one hundred at retrieval. Such a value describes citations linked through the source's deposited references and should not be equated with a Scopus or Web of Science count. Records can differ in citation coverage as well as age and subject. A single summary statistic also conceals the skewed distribution characteristic of citation data. The median is therefore reported as a descriptive property of the archived snapshot rather than a benchmark for publication quality.

The historical paper on evolution and revolution had 965 recorded citations, the largest count among the selected records. Its earlier publication date provided a longer period for accumulating citations than the recent records. The title also indicates a broad conceptual remit that may attract attention from different applications. These observations offer plausible

interpretive considerations without identifying the reasons for each citation. A high count establishes recorded visibility, not agreement with every argument in the cited paper (Roll & Wylie, 2016).

The three-paradigms paper and the application-and-theory-gaps paper had 698 and 689 recorded citations respectively. Their conceptual titles suggest why a bibliometric sample may contain publications that serve as organising references rather than evaluations of one intervention. The current data do not distinguish supportive, critical, or perfunctory citations. Interpreting all citations as endorsements would require information that the count field does not contain. Citation-context analysis would be needed to investigate how these publications are used (Chen et al., 2020; Ouyang & Jiao, 2021).

The personalised-education review had 497 recorded citations, and the higher-and-adult-education literacy review had 494. These counts place them among the more visible records in the selected sample, but they do not establish that reviews are more influential than empirical studies generally. The sample is too small and selection-dependent for that conclusion. Their titles identify different synthesis objects, making it necessary to distinguish citation visibility from the substantive evidence each review evaluates (Bhutoria, 2022; Laupichler et al., 2022).

Teacher-related publications also span several objects that citation counts alone cannot combine meaningfully. Barriers in Hong Kong schools, teacher preparedness, and university instructor experiences concern different institutional and educational settings. Ranking these records by citation count would not indicate which findings transfer to another setting. The descriptive profile should instead retain their metadata and declared research objects so that any later comparison can be grounded in an explicit question about relevance and transfer (Cheah et al., 2025; Cheng & Wang, 2023; Kohnke et al., 2023; Wang & Cheng, 2021).

An assessment title comparing expert tutors with generative artificial intelligence illustrates a further limit. The title identifies a comparison, but metadata alone cannot establish its measurement quality, sample size, or educational consequences. A highly visible assessment paper would still need substantive appraisal before informing institutional decisions. The same principle applies to titles about learner competencies or attitudes. Bibliometric indicators help locate research; they do not replace evaluation of the evidence it reports (Awidi, 2024; Sanusi et al., 2022; Turós et al., 2025).

The main methodological limitations arise from relevance ranking, the phrase-matching rule, a fixed stopping point, source-specific citation coverage, and title-only coding. The sample excludes relevant records that use abbreviations or different terminology and overrepresents the outlets favoured by the query. No claim of exhaustive coverage, global growth, thematic saturation, or causal influence follows from these data. These restrictions are explicit because a precisely calculated table can still be misleading when its population is poorly described.

The study demonstrates a reproducible way to report a limited bibliometric exercise without expanding its conclusions beyond the data. The thirty-record corpus displayed outlet concentration, a recent publication cluster, and varied educational objects. Its value lies in the connection between those results and an inspectable retrieval rule. Future work can extend the design through a complete multi-database search, richer semantic coding, author disambiguation, and citation-context analysis, each of which would address a specific limitation rather than merely produce a larger diagram.

CONCLUSION

The analysis of 30 Crossref records identified a pronounced concentration in two specialised journals, with 26 publications originating from *Computers and Education: Artificial Intelligence* and 25 records dated between 2022 and 2025. Title-based classification showed relatively frequent references to school education, teachers, literacy, and generative artificial

intelligence, whereas terminology associated with ethics and rights appeared less frequently. These distributions establish the bibliographic characteristics of the selected corpus but provide no basis for estimating research prevalence, publication growth, or thematic priorities across the wider field. The concentration of records within journals whose titles overlap the search expression also identifies a potential interaction between retrieval design and observed publication distributions, although the available analysis does not isolate the contribution of Crossref's ranking mechanism.

The principal methodological contribution concerns the distinction between bibliographic visibility and the underlying structure of scholarly research. A documented search procedure can produce reproducible descriptive indicators while remaining sensitive to query formulation, relevance ranking, restrictive eligibility conditions, and sample boundaries. The findings establish that methodological transparency does not eliminate selection effects but permits their consequences to be identified and interpreted within defensible limits. Further investigations can assess these effects through alternative search expressions, unrestricted Crossref retrieval, comparisons with Scopus and Web of Science, and lexical classification extending from titles to abstracts and full texts. Such comparisons would establish whether the observed concentration persists across retrieval strategies and provide a stronger basis for evaluating the substantive distribution of artificial intelligence education research.

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