



Generative artificial intelligence in education: Mapping research trends and future directions

Larisa Y. Lutskovskaia ¹

 0000-0002-4806-6610

Oksana Chigisheva ²

 0000-0003-3358-2898

Vagiz G. Gimaliev ³

 0000-0003-2758-6972

Sergei P. Zhdanov ^{4*}

 0000-0002-1330-8165

Valeria L. Zakharova ⁵

 0000-0001-5407-6906

Lyudmila M. Smirnova ⁶

 0000-0002-6581-4529

¹ Foreign Languages Department, People's Friendship University of Russia – RUDN University named after Patrice Lumumba, Moscow, RUSSIA

² "Foreign Languages" Department, Moscow Polytechnic University, Moscow, RUSSIA

³ Department of Foreign Languages №2, I. N. Ulianov Chuvash State University, Cheboksary, RUSSIA

⁴ Department of Criminal Law, Procedure and Criminology, National Research University "Higher School of Economics" (HSE University), Moscow, RUSSIA

⁵ Department of Medical and Social Assessment, Emergency, and Ambulatory Practice, Sechenov First Moscow State Medical University, Moscow, RUSSIA

⁶ Department of Dermatovenereology, Sechenov First Moscow State Medical University, Moscow, RUSSIA

* Corresponding author: zhdanov120009@yandex.ru

Citation: Lutskovskaia, L. Y., Chigisheva, O., Gimaliev, V. G., Zhdanov, S. P., Zakharova, V. L., & Smirnova, L. M. (2026). Generative artificial intelligence in education: Mapping research trends and future directions. *Contemporary Educational Technology*, 18(4), Article ep701. <https://doi.org/10.30935/cedtech/19639>

ARTICLE INFO

Received: 12 Aug 2026

Accepted: 3 Oct 2026

ABSTRACT

Generative artificial intelligence (GenAI) recently appeared as an issue of its time which has been changing the educational landscape at a considerable rate and opening new pathways and challenges for educators and learners. Therefore, in terms of GenAI for education this bibliometric analysis will characterize the change and development by mapping trends and patterns, examining prevalent subject areas in academia interest. Following the established criteria, we ran a systematic search on Scopus database with the identification and analysis of 121 peer-reviewed documents (journal articles, review articles and conference papers; selection reported with reference to the PRISMA 2020 guideline) published between January 2023 and March 2025 related to GenAI applied in education. The thematic labels attached to the algorithmically generated VOSviewer clusters were assigned by the researchers, and interpretations of regional patterns are presented as tentative. The article features papers discussing ways to use GenAI in learner-centered teaching, curriculum development and assessment. The findings reveal a rapid increase in research output between 2023 (23 articles) and 2024 (67 articles), followed by 31 articles in the first quarter of 2025, and substantial international collaboration (34% of the articles). Moreover, the thematic analysis shows that pedagogical integration and instructional design (55.4% of the articles), assessment and academic integrity (44.6%) and ethical and societal implications (39.7%) are the most prominent themes, with a shift from ethical and assessment concerns in 2023 towards pedagogical

integration and learning outcomes in 2024-2025. Research affiliated with the United States, the United Kingdom, China and Germany dominates the corpus, whereas research from Latin America and Africa appears under-represented. The review proposes future directions of research and spells out an array of issues that have until now gone unexamined by helping the reader enter the intellectual landscape of GenAI in education. The bibliometric evidence indicates growing scholarly attention to the potential of GenAI in education; this study did not appraise the quality of the evidence on learning outcomes. Nonetheless, designers are being asked to collectively conduct further research to address any potential negative effects of the technology, and create useful design frameworks, to implement this technology into the education system worldwide, without compromising on justice and morality.

Keywords: artificial intelligence, education, bibliometric review, Scopus

INTRODUCTION

The rise of generative artificial intelligence (GenAI) is more than just a game changer in the educational technology sector. It is essentially transforming the modes of knowledge creation, dissemination and assessment taking place in present-day educational environments (Chen et al., 2020; Kasneci et al., 2023). Previously, the focus of educational technology activities was to facilitate the application of knowledge. However, GenAI can create new content, carry on complex conversations, and customize learner responses in an unprecedented way (Baidoo-Anu & Ansah, 2023). It is a technological revolution which attracts huge scholarly attention. The research papers are growing exponentially on the GenAI and education in question (Sullivan et al., 2023).

GenAI is a term that encompasses a wide variety of technologies. The subclass choice usually relies on the medium used. The most common AI tools used for creation purposes include large language models (LLM) like GPT-4, BERT and their variants, image generators like DALL-E and Midjourney, and multimodal AI which can take in and out various kinds of content (Rudolph et al., 2023). GenAI systems are based on deep learning architectures, mostly on the transformer models, for generating more human-like text, images code and many other forms of creative output which can beneficially incorporate in the pedagogical practice (Dwivedi et al., 2023). The sophistication of current GenAI may be so high that it may already be used to solve confusing cognitive problems and offer personalized platforms of education (Bommasani et al., 2021).

The impact of GenAI in education can be seen in diverse areas of the learning ecosystem. AI-based tutoring systems at the instructional level have the capacity to provide students with immediate feedback that is personalized as well as ability to adapt the content and modality of presentation relative to learner's individual pattern of performance (Holmes & Tuomi, 2023). GenAI helps in designing syllabus by providing systems to create learning materials, generate questions for assessment, and engineer learning interventions to learner development in a live manner (Grassini, 2023). In administrative work processes, the AI systems are working on automating grading, scheduling, and resource allocation so that teachers can spend more time working innovatively and collaboratively directly with learners (Chan & Hu, 2023).

The rapid rise of GenAI in the field of education has also raised a number of controversies regarding its ethical issues, possible abuse, and the net effect on the main objectives of education (Tlili et al., 2023). According to Sullivan et al. (2023), the challenge of maintaining academic integrity is made even more challenging due to the use of contemporary AI technology by students. This technology can generate quality written work, solve difficult problems, and even produce creative content. The ability of AI to produce quality human-like products makes it challenging to distinguish between AI-generated and human-created products. According to Holmes et al. (2023), the problem of data privacy, algorithm bias, and its potential to replicate or create greater educational inequalities.

In the traditional sense, the learning of different students could not be measured using AI systems as frequently as necessarily which did not allow instructors to alter their assessment practices. GenAI systems, on the other hand, can respond to questions and handle completions. To become more assessment aware, you will need to change your assessment strategies to focus much more on students presenting their own messages (which are higher order thinking, creativity, etc.).

In order to improve education, GenAI should change the educational paradigm, meaning that education goals and methods should be redefined. The crucial characteristics of the teacher must be reshaped so that

they are not in conflict with the AI potential but rather supplement them (Warschauer et al., 2023). The literature calls for new paradigms of meaningful learning in the AI-enhanced world and adaptive learning institutions must enable students to learn what should be taught (Baidoo-Anu & Ansah, 2023).

Although the area of GenAI application to education has been growing in popularity, a synthesis of the available studies has not been completed yet, which would chart the intellectual field, pinpoint the key players and themes involved, and outline the areas that need further research. Bibliometric analysis offers an organized approach to filling this gap by performing a quantitative analysis of patterns of publications, citation networks, and thematic clusters in a research area (Donthu et al., 2021). It is an effective method that allows the researcher to find influential works, track the history of ideas, see how networks formed, and reveal new trends that can influence the way researchers will operate further (Zupic & Čater, 2015).

Recent research reveals the impact of GenAI on educational development, and its potential cannot be underestimated. Certainly, its potential is noteworthy and an important resource to utilize. Nonetheless, education has largely been unexplored through GenAI, with no systematic mapping having been done. The minimum level of information needed for evidence-based decision-making at the educational field level by the increasing community of practitioners and researchers has not yet been met. The present research meets this requirement by performing a comprehensive bibliometric analysis of the research works published on the use of GenAI in education.

LITERATURE REVIEW

Theoretical Foundations of AI in Education

The systematic and organized implementation of the AI in the educational sphere is guided by several theories that are known to shape our concepts of the learning, thinking, and design. The constructivist learning theory is one of the most popular ones. This reiterates a learner-centered approach where the learner is an active participant in the process of building the knowledge. As Holmes and Tuomi (2023) mentioned, AI-enabled adaptive learning systems have the ability to develop an individual learning journey through the above-discussed theory. Through proper construction, GenAI can be an engaging alternative to implementing the different AI tools as cognitive scaffolds in an educational environment to facilitate learners in improving their zone of proximal development as theorized by Vygotsky (Kasneci et al., 2023). Mayer (2021) is another author who created the cognitive principle of multimedia learning. The current article provides partial information on how effective education tools may be produced based on GenAI and maximize cognitive load, resulting in improved learning processes. The extraneous cognitive load can be reduced and germane cognitive processing can be enhanced due to the fact that GenAI systems generate multimodal content including a visual, a textual, and an interactive element (Grassini, 2023). In the paper, Chan and Hu (2023) state that the application of these principles in practice related to the AI-generated content should be performed carefully and efficiently. This is required in regard to the manner, through which learners view information, which is created on the machine and human being.

Another theoretical prism of viewing the role of GenAI in the education sector is self-regulated learning frameworks. It in the self-regulated learning model offered by Zimmerman (2002) has paid attention to the cyclic process led by the goal setters, progress monitors and strategy modifiers, in which learners strive to achieve the set goals. Theoretically, it is possible to use AI systems at every level of this process because the system could assist the learners in making the goals of the learning process clearer, giving them timely feedbacks on the progress, and proposing other approaches in case the current ones did not work, which might be ineffective (Tlili et al., 2023). An interesting empirical issue is the degree to which the self-regulation skills can be facilitated or, vice versa, impeded by the AI-based learning.

AI Technology Evolution in the Education Industry

The implementation of the AI in the learning process has thus taken a somewhat divergent form in the recent decades, abandonment of the rule-based expert systems, to the more advanced machine learning models, which even can produce new content, they can even talk the natural language. The rule-based reasoning applied in early intelligent tutoring systems (ITS) like the SCHOLAR and MYCIN-Tutor to offer

instructions in small closed scaled environments (Woolf, 2010). Such systems established that individualized instruction was possible, but the limitations to their use in education were the poor knowledge representations and failure to address incidental student response.

More flexible and adaptive educational technologies became possible in the 1990s and 2000s with the introduction of machine learning techniques. The knowledge tracing and variations of it enabled the systems to describe student knowledge state probabilistically to make more flexible instructional paths flexible (Corbett & Anderson, 1994). The creation of recommendation systems led to the development of collaborative filtering algorithms that could enable educational systems to give recommendations about the learning materials with regard to the interest and the effectiveness of the learners of the same types (Manouselis et al., 2011). Irrespective of these advancements, a majority of the educational technologies offered by pre-GenAI were focused on selection and sequencing of already existing content rather than creation of new teaching resources.

The development of deep learning as well as transformer acceleration of models has changed the future of AI systems in learning solely. LLMs can also be used to generate them in answering open-ended questions using realistic and coherent responses, writing on complex topics in various formats, and even conducting Socratic dialogue to assist learners in learning (Kasneci et al., 2023). The capabilities are more than the limitations of the former AI systems and can be taught to develop applications that are more like human tutors with regard to their ability to change themselves based on their environment. Nevertheless, as the respective functional enhancement comes, new challenges emerge of proper content, instructional aptness, and a prospect of obtaining proper-sounding faulty data with the aid of AI systems (Bommasani et al., 2021).

Current Applications of GenAI in Education

The latest AI generation in education can be applied in different fields, such as content creation and personalized tutoring, evaluation, and administration. AI systems have the potential to generate different kinds of learning resources, including lesson plans, practice problems, and explanatory text with the aim of meeting a given learning goal and level of student proficiency (Baidoo-Anu & Ansah, 2023). The language learning apps are based on GenAI which can be used to generate practice opportunities in conversations and give a learner a chance to participate in a realistic dialogue and receive immediate feedback on their language production (Rudolph et al., 2023).

Another important area of application is ITS which are driven by GenAI. Such systems are able to involve students in prolonged conversations, provide answers to questions using contextually fitting explanations, as well as change their instructional strategy according to interactions with students (Holmes & Tuomi, 2023). GenAI tutors, unlike the past generation of tutoring systems which is limited by pre-programmed responses library have the ability to respond to unexpected questions and generate novel explanations on demand creating potentially a more dynamic and responsive learning experience (Sullivan et al., 2023).

One of the opportunities (and challenges) to GenAI in education is the assessment of it. On the one hand, AI systems have the ability to produce a variety of questions for assessment, give more concrete feedback regarding the work of students, and even mark complex questions (such as essays) with a high level of precision (Chan & Hu 2023). The converse is the availability of the students to the powerful GenAIs able to handle the assignments makes some key questions regarding the academic integrity and validity of the traditional methods of assessment (Tlili et al., 2023). Teachers are wanting to consider other assessment methods which can use AI as a learning tool which still can assess the real student abilities (Warschauer et al., 2023).

Educational Implications and Challenges

The emergence of GenAI in education imposes significant alterations in the teaching process and raises some important questions regarding the nature and the role of education. Traditional systems of teaching that enable dedicating attention to the knowledge transfer and practicing rote may prove to be less useful since AI can easily access objective information and perform simple tasks in a human brain (Holmes et al., 2023). Such a shift makes teachers think about what skills and competencies students must develop in the world of AI augmentation and, perhaps, focus more on critical thinking, creativity, ethical thinking, and abilities to work well with AI systems (Kasneci et al., 2023).

AI literacy has become an important educational objective and it presupposes the ability, not only to become skilled with the use of AI tools, but also to be familiar with their opportunities, limits and social implications (Long & Magerko, 2020). Educators ought to help students develop skeptical views on AI-generated content, including becoming able to evaluate its plausibility, recognize potential bias, and understand what processes the outputs of AI are founded on (Bommasani et al., 2021). It also dictates the necessity of training the educators and making them AI literate, which is not an easy task because of the high technological innovation rate and the overall absence of career advancement opportunities (Grassini, 2023).

The second pedagogical question is the contribution of teacher in AI-enhanced learning settings. GenAI is no longer being viewed as a substitution of human educators, but rather as a learning assistant by automating the low-value part of the teaching process, and also by tailoring the learning process and offloading teachers with low-value teaching workloads in favor of high-value teaching and learning (such as mentoring, facilitating discussion and addressing the social-emotional needs of learners) (Chan & Hu, 2023). However, in order to transform this vision into a practical experience, the focus on the design and application of AI systems should be significant and sufficient attention should be paid to their implementation, which should not exclude the human factor in teaching and learning but rather support it (Holmes & Tuomi, 2023).

Ethical Considerations and Equity Concerns

The implementation of GenAI educational institutions introduces significant ethical issues, which are worth paying close attention to by researchers, practitioners, and policymakers. Among the primary issues, the problem of the bias in the algorithms should be listed, as educational access and achievement are already unequal, and the bias in the systems that are trained on it might cause the existing inequities to even escalate (Tlili et al., 2023). Language models may be more effective in terms of accommodating the work of textual expressions in standard dialects and it may be somewhat discriminatory against students of linguistic minorities. Similarly, training data which fails to reflect certain aspects of cultural perspectives may result in development of AI generated content which may not be appealing and supportive to support a diverse range of student cohorts in a sufficient manner (Holmes et al., 2023).

Data privacy and security is another major GenAI ethical concern in the education sector. In order to be productive, AI systems require big amounts of data, which prompts the query of what type of information should be collected about learners, how and where such data should be stored and preserved, or to whom this data should be accessible (Dwivedi et al., 2023). Such potentials of the educational AI systems to collect a lot of data about the learning process, challenges and even moods of the learners result in an opportunity of personalization and contributes to the risk of surveillance and disclosure of secret information (Sullivan et al., 2023).

The presence of sophisticated AI generators that students can use to present their work has contributed to academic dishonesty. On the one hand, some think that it results in a crisis that has to be discovered by implementing a system of detection and punitive methods; on the other hand, some individuals argue that the idea of academic integrity should be reevaluated in the context of the existence of AI and that they should be given an assignment in which they can showcase their learning with veracity and be given the opportunity to apply AI tools appropriately (Warschauer et al., 2023). The argument is a subset of more broad arguments related to education and its role, and what sort of assistance might be considered acceptable when it comes to student work (Baidoo-Anu & Ansah, 2023).

The ethical issue concerning the contribution of GenAI to the creation of educational disparity is a potentially disastrous issue. The under-resourced communities and schools can introduce new digital inequalities by experiencing a limited access to advanced AI tools, access to the internet, and ability to access the most advanced devices that can process AI applications (Tlili et al., 2023). Besides, one cannot consider GenAI to be a resource that can be used in the learning process without technology and digital literacy and assistance to use the tools effectively, which in educational practice may also be disproportionately distributed (Holmes et al., 2023).

METHODOLOGY

Research Design and Rationale

The study design in this research is bibliometric study in order to utilize systematic literature review of scholarly literature regarding GenAI in education. The use of bibliometric analysis is a quantitative approach to the investigation of large volumes of literature, which enables determining the trends of publications, the influence of authors and institutions, networking of authors and institutions, and patterns of the theme within a research area (Donthu et al., 2021). This research design would be particularly beneficial to examine the rapidly transforming issues, including GenAI in education, the number of publications has grown exponentially in the last several years, and the classic narrative reviews are getting harder and harder to implement (Zupic & Cater, 2015). The identification and screening of records were reported with reference to the PRISMA 2020 reporting guideline (Page et al., 2021), as far as the recorded data allow; however, the analysis itself is bibliometric (performance analysis and science mapping) and does not synthesize the findings of the included studies.

There are a number of advantages to doing so using the bibliometric technique, as regards the intellectual organization of the GenAI works to the field of learning. First, it provides objective data-driven overview of field as per patterns of publications and citation as compared to the subjective selection of the literature (Cobo et al., 2011). Second, it also enables finding cross-boundary networks and knowledge circles between researchers, institutions, and nations and the socialization of scientific production in this field (Aria & Cuccurullo, 2017). Third, they may be disclosed through the assistance of bibliometric methods that can potentially identify certain thematic clumps and emerging issues which could not be easily identified under the assistance of the traditional method of literature review (Chen, 2006).

Data Source and Search Strategy

The Scopus database was taken as the primary source of data in the library in this bibliometric analysis due to offering a broad variety of peer-reviewed sources related to different fields, possessing only credible publications, and easy to carry out a bibliometric analysis due to its well-developed metadata (Baas et al., 2020). In this regard, despite having other similar databases that offer an alternative source of bibliographic information such as Web of Science and Google Scholar, Scopus database has offered the most appropriate combination of coverage, quality control and analysis in this context of this study (Burnham, 2006).

The search strategy was developed in a manner that allowed selection of the scholarly publications that had researched on the use of GenAI in education, but at the same time was narrow to eliminate irrelevant searches.

The search query below was created and narrowed down in the following way: TITLE-ABS-KEY ("generative AI" OR "generative artificial intelligence" OR "large language model*") AND TITLE-ABS-KEY (education* OR learning OR teaching OR pedagogical* OR curriculum OR instruction* OR assess* OR student* OR school* OR university OR "higher education") AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (LANGUAGE, "English")). The publication-date window (1 January 2023 to 31 March 2025) was applied as a filter on the results.

The databases that the search was conducted were restricted to the Scopus document types "article", "review" and "conference paper" (i.e., peer-reviewed journal articles, review articles including systematic reviews, and conference papers) published between January 1, 2023, and March 31, 2025, and in English. The publication window therefore covers 2023, 2024 and the first quarter of 2025; cumulative citation counts are reported as of December 2025. Document types outside these categories (books, book chapters, editorials, letters, notes, short surveys, errata and retracted publications) were not eligible. This time limit was decided upon due to the fact that GenAI technologies, specifically LLMs such as GPT-3.5 and GPT-4, became highly accessible to educators and researchers only at the end of 2022 and the beginning of 2023, which led to the explosion of educational research investigating these technologies. Conference proceedings were also utilized to include upcoming research, which may not be present yet in journal publications, given the fact that fast changing fields usually have their first publication in conference formats (Franceschet, 2010).

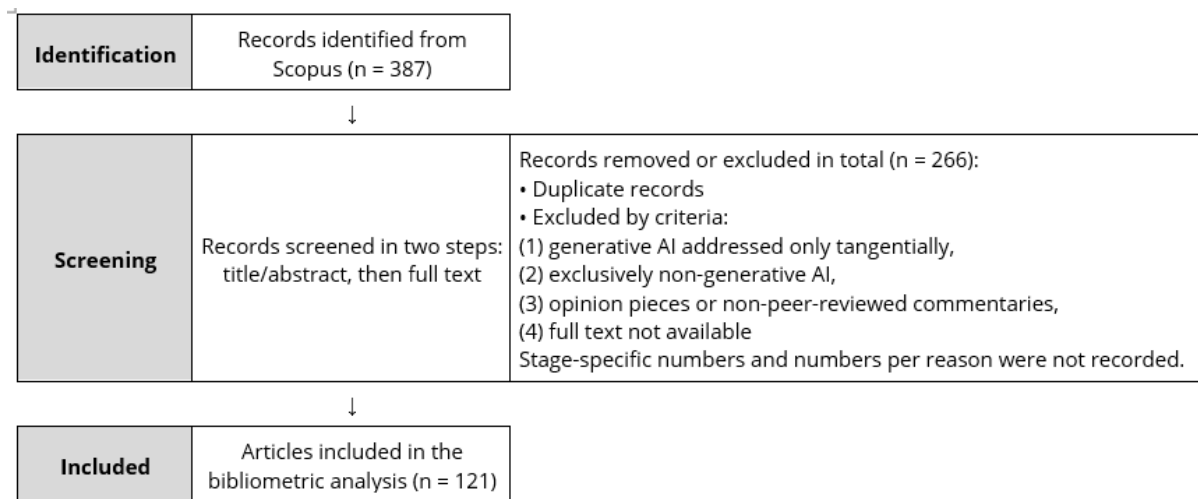


Figure 1. Simplified PRISMA 2020 flow diagram (the authors' own elaboration)

Inclusion and Exclusion Criteria

The publications that were included in the final analysis were those that met the following criteria:

- (1) their main focus was on GenAI technologies or their usage,
- (2) the article was presented in the educational setting (K-12, higher education, professional training, or informal learning),
- (3) presented empirical research, conceptual frameworks, or review studies (including systematic, scoping and bibliometric reviews), and
- (4) were published in English as peer-reviewed journal articles, review articles or conference papers, which correspond to the document types retrieved from Scopus.

Articles were filtered out when:

- (1) they referred to GenAI only tangentially without discussing it in depth,
- (2) were exclusively about non-GenAI technologies (e.g., traditional machine learning classifiers and rule-based systems),
- (3) they were opinion pieces or non-peer reviewed commentaries (including editorials and letters), or
- (4) were not in full text.

To resolve any ambiguity between the inclusion criteria and the document-type restrictions, systematic reviews (and other secondary studies) on GenAI in education were eligible for inclusion, provided that they were published as a peer-reviewed journal article, review article or conference paper and met criterion (1) and criterion (2). They were retained because the aim of this study is to map the scholarly output on the topic rather than to synthesize primary empirical evidence; secondary studies are therefore part of the body of literature being mapped. Conversely, systematic reviews that were not peer-reviewed (e.g., preprints or reports) were excluded. For brevity, all eligible documents are hereafter referred to as "articles". Because review papers synthesize and cite primary studies, their inclusion may inflate citation counts and thematic overlap, which is acknowledged in the limitations.

The first search provided 387 articles that were potentially relevant. The selection process is reported with reference to the PRISMA 2020 statement (Page et al., 2021), as far as the recorded data allow, and the flow of records is shown in [Figure 1](#). After the deletion of duplicates and the use of inclusion/exclusion criteria due to the two-step screening (title/abstract review and full-text analysis), 121 articles were kept in the final bibliometric analysis. The total number of records identified (387) and included (121) is known, which implies that 266 records were removed or excluded across the two screening steps (duplicates, title/abstract exclusions and full-text exclusions). The numbers removed or excluded at each separate step and for each reason were not recorded during screening and therefore cannot be reported (see limitations); [Figure 1](#) accordingly presents a simplified PRISMA 2020 flow diagram limited to the numbers that can be reported.

Two reviewers were used in this selection process and in case of disagreement, a third reviewer was consulted and a discussion was made between the two reviewers. The screening process had a high inter-rater reliability (Cohen $\kappa = 0.89$), which implies that there was great agreement among the reviewers.

Data Extraction and Processing

To both of the articles used, Scopus provided much bibliographic data, including title, authors and their affiliation, year of publication, name of the journal or conference, abstract, keywords, number of citations, source of funding (where applicable) and references to the same. In other metadata, document type, is open access, subject area and other metadata were also captured. This was later exported in CSV and BibTeX format to be further analyzed.

Bibliometric indicators were also compatible and right to the point as the data itself was cleaned and preprocessed. Authors names were also combined in such a way that the variations in a layout and a sequence of names are considered. The differences were adjusted according to the affiliation of institutions (e.g., IT and Massachusetts Institute of Technology). The key word mining was carried out using both authors given keywords and intelligent key word mining using the natural language processing strategies utilizing the titles and the abstracts of the articles. This bi-directional design gave thematic coverage of material and was one of the ways of not encroaching on the designation of the major concepts by the authors.

Analytical Techniques

To give them some free information regarding the organization and formation of the GenAI research in education, the following bibliometric tools were used to interpret the results obtained: The productivity measures in Performance Analysis were the number of publications annually, the most prolific authors, the institutions and countries which have produced the most publications and the publications cited most. The effect and the impact of individual articles, authors and journals were quantified using the total number of citations and average number of citations per year as well as values of h- index. Such analyses provide a clue of the most impactful input to the field and people in the field who would allow the field research developments.

The representation of intellectual structure and the thematic composition of the area of research was carried out through science mapping. The co-authorship analysis allowed to give an understanding of collaboration patterns and knowledge flows (collaborators, institutions, countries). The co-cited sets that were found through the co-citation analysis were providers of the general intellectual traditions and theoretical courses present within the field. The thematic groups of thematic separation of connections between different topics of researches have been determined through the analysis in terms of co-occurrence of key words.

Temporal Analysis paid attention to the evolution of the field during the period under study, asking what changes were as follows,

- (1) quantity of publications and
- (2) modification of both citation and thematic focus patterns.

Chronological perspective enabled us to determine emergent themes and subjects of interest in research and the themes that have been the focus of scholars over the years.

Analytical Tools

A bibliometric analysis has been performed with the aid of a set of particular software tools, each of which has been selected because of its particular features in processing various types of bibliometric data. The co-authorship networks, co-citation maps and key-word co-occurrence networks were created and visualized using VOS viewer (version 1.6.19) (van Eck & Waltman, 2010). The algorithms of cluster analysis and visualization of this tool is best suited to find thematic clusters and make connections between the clusters.

Comprehensive bibliometric analysis, which covered the performance measures, time series and other techniques for science mapping, was performed using R statistical environment (version 4.3.1) with the bibliometrix package (version 4.1.0) (Aria & Cuccurullo, 2017). The package is a complete collection of functions that are created with a focus on bibliometric research and allows the reproducible workflows of the

analysis. In order to perform the data cleaning, some initial descriptive statistics and a few visualizations creation, Microsoft Excel was used. In order to determine the influential nodes and structural features of collaboration networks, network analysis measures were determined (degree centrality, betweenness centrality and clustering coefficients). Keyword co-occurrence and co-authorship networks were mapped and clustered with VOSviewer (van Eck & Waltman, 2010).

Cluster Formation and Thematic Labeling

Cluster formation

Clusters were generated algorithmically by VOSviewer, which places items (keywords or authors) on a two-dimensional map according to the strength of their associations and assigns each item to a cluster by means of a modularity-based clustering technique (Waltman et al., 2010). For the keyword co-occurrence analysis, both author-provided keywords and keywords extracted from titles and abstracts (see data extraction and processing) were used; the full counting method and association-strength normalization were applied, and only keywords occurring at least 4 times were retained. Synonyms and spelling variants (e.g., “large language model” and “large language models”) were merged with a thesaurus file, and generic terms and the search terms themselves were removed. Clustering was run with the default VOSviewer settings (resolution = 1.00; minimum cluster size = 1). VOSviewer clusters are therefore purely statistical groupings of items that frequently co-occur or collaborate; they carry no inherent meaning or label, and their number and composition depend on the parameters chosen.

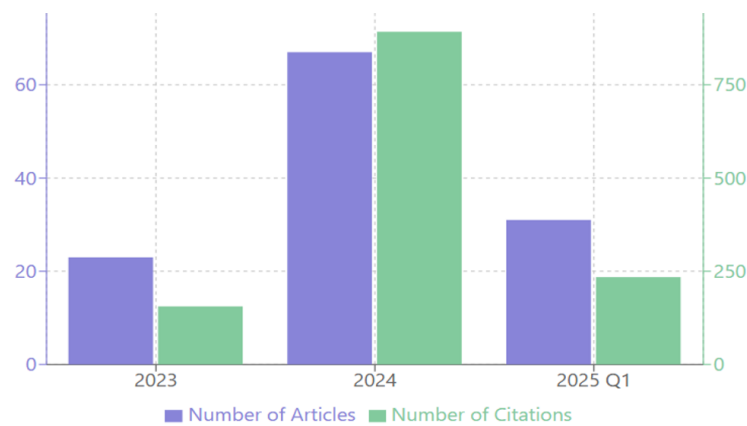
Thematic labeling

The thematic labels reported in the findings section (e.g., pedagogical uses and instructional design and assessment and academic integrity) are interpretive categories assigned by the researchers and are not outputs of VOSviewer. Labeling followed three steps. First, two authors independently examined the highest-frequency keywords of each algorithmically generated cluster, together with the titles and abstracts of the most representative articles and proposed a descriptive label. Second, disagreements were resolved through discussion (a third reviewer was consulted when needed), and labels were merged where clusters were conceptually overlapping. Third, each of the 121 articles was assigned to one or more of the resulting themes on the basis of its title, abstract and keywords; because an article may address more than one theme, the article counts and percentages reported for the themes can sum to more than 121 (100%). Theme labels and article-level theme counts therefore reflect researcher judgment, and alternative labeling could be defended, whereas the VOSviewer clusters indicate only the statistical proximity of keywords. Likewise, the descriptive labels attached to co-authorship clusters (e.g., European ethics cluster) summarize the predominant affiliations and keywords within each cluster and were added by the researchers; the algorithm grouped authors by collaboration links only.

Limitations and Ethical issues

There are a number of weaknesses of this bibliometric study that should be mentioned. First, this in turn is causing any other research being published elsewhere in ones not included within this database to be removed, which can lead to selection bias. Nonetheless, the coverage of non-peer-reviewed materials in Scopus is richer in terms of conferences and journal resources, and this issue is to a great degree mitigated. Second, the emphasis on the English-language publications does not include the potentially important research on the topic that was published in other languages that could be especially important in explaining how the world views GenAI in education. Third, the temporal focus expands (January 2023-March 2025) limit itself with the first wave of researches as a reaction to the recent developments in the field of GenAI, and the fast pace of the evolution in the field implies that results can become obsolete quite soon. Moreover, 2025 is represented only by its first quarter, so year-to-year comparisons involving 2025 (publication counts and mean citations) should be interpreted cautiously.

Use of citation counts as measures of impact because of inherent bias because highly cited work might not be the most important or methodologically sound work, and recently published work might not have had time to accumulate citation as compared to published work of longer age. In order to overcome this



Note: Citation data represents cumulative citations received through December 2025

Figure 2. Number of articles and citations per year (2025: January-March only; cumulative citations as of December 2025) (the authors' own elaboration)

shortcoming, we have attempted to take into consideration several measures of impact and have studied citation velocity (citations per year) and total citation.

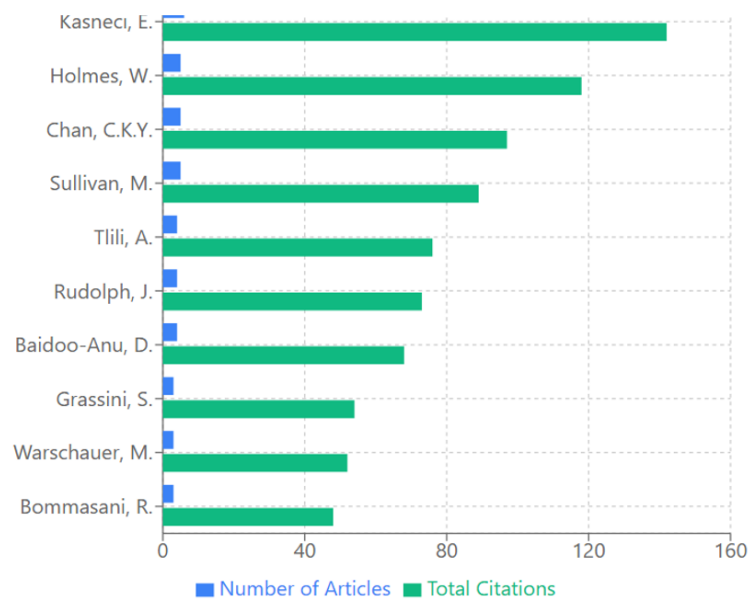
In addition, regional and institutional patterns were derived from author affiliation data of English-language, Scopus-indexed documents only. Country counts reflect author affiliations and do not show where studies were conducted or which populations they concern, and Scopus coverage and the English-language restriction are likely to under-represent research from Latin America, Africa and parts of Asia. The explanations offered for regional, institutional and funding patterns (e.g., infrastructure, funding, policy, or institutional capacity) are plausible interpretations informed by the literature rather than findings that the bibliometric data can test, and they should be read as tentative. Finally, VOSviewer clusters depend on the parameters chosen, the thematic labels are researcher-assigned, and the inclusion of review papers may inflate citation counts. Finally, the numbers of duplicate records and of records excluded at the title/abstract and full-text stages (and for each exclusion reason) were not recorded during screening; the PRISMA flow diagram therefore reports only the records identified (387), the total removed or excluded (266) and the final sample (121). Agreement statistics for the article-to-theme assignment are not reported. This limits the transparency of the selection process, although the search string, filters, eligibility criteria and the two-reviewer procedure are fully reported.

With regard to ethical issues, in this study, the review of just publicly available bibliographic information was included and it does not require the approval of an institutional review board. Nevertheless, we made sure that we did ethical research by not cherry picking to report but rather faithfully reporting the works of the authors and furthermore we admitted that our research had limitations. All the data sources and analytical methods have been well recorded to allow our findings to be repeated and verified.

FINDINGS

Trends in Publication and Citation

The synthesis of the patterns of publications and citations indicates impressive dynamics of the increasing scholarly interest in the field of GenAI in education within the short time frame considered. The 121 articles in this study are shown to be growing rapidly in research output, with 23 articles in 2023, 67 articles in 2024, and 31 articles in the first quarter of 2025 (Figure 2). The 2025 figures cover only the first quarter (January-March 2025). This trend indicates that 2024 was a high point in the emergence of early research reactions to the broad usage of GenAI devices in education, and the field can still be seen as actively developing with enthusiasm in early 2025. The 121 articles have received 1,282 cumulative citations as of December 2025, with large disparities between the number of citations in each of the publications. The article which has been the most cited was found with 87 citations and the median citation number was 8. Publications of 2023 had a mean of 6.78 citations per article, 2024 publications mean of 13.31 citations and 2025 publications mean of



Note: Citation counts represent total citations for all articles by each author

Figure 3. Distribution of the most prolific authors (the authors' own elaboration)

7.55 citations. The fact that the average of 2024 publications has been higher, even though they were published more recently, means that this group has several well- impactful works that quickly entered the world of recognition in research community.

The reference path shows a rising momentum of impact as monthly citation counts are expected to rise in 2023 (around 13 citation per month) to approximately 74 citations per month in 2024. This trend of growth suggests that it is not only the volume of publications that is increasing, but also the interest in the current literature because researchers will use previous publications to develop the discipline. The pattern of the citation distribution has the characteristics of the power law used in the scientific literature, where small number of highly cited papers in the literature gets a disproportionate attention and many publications in the literature get relatively low citation counts.

Recognition of Authoritative Writers and Co-Authorships

As the productivity of the authors was discussed, one can point out that the distribution of contribution is not very uneven, and no particular one of the authors has controlled the field. The most active in terms of publishing the books in the period of study were authors with 3 to 6 articles without any researcher being in excessively high dominance. The author with the largest number of publications 6 was Kasneci, E. followed by Holmes, W., Chan, C. K. Y. and Sullivan, M. with 5 publications each. The authors are different in terms of institutional belonging to the region and prove that the interest in the research of GenAI and education is global (Figure 3). The network analysis of the co-authorship shows that collaboration work in the direction is high with 67 percent of the articles keeping over one author and the average number being 3.2. Network visualization also showed that there were many distinct collaborative groups, suggesting that there are established research groups that address the same issues regarding GenAI in learning. The question of ethical implication and policy framework of AI in education is being focused on by the largest research group (23 researchers; most of them are European institutions based). The second big cluster of 19 scholars locates primarily in North American institutions and they are interested in the real research on interactions between students and GenAI tools. A third cluster of 15 researchers are mostly based in institutions in the Asian countries and are interested in technical development of AI-based learning programs (Figure 4) International collaboration has 34% multinationals in the articles. International collaboration of researchers of the United States and United Kingdom researchers (18 collaborative publications) and United States and researchers of China (12 collaborative publications) and German and Dutch workers (9 collaborative publications) were the most widespread. These tendencies suggest the already established international research networks that are likely to be facilitated with the help of institutional relationships, common research interest, and the globality

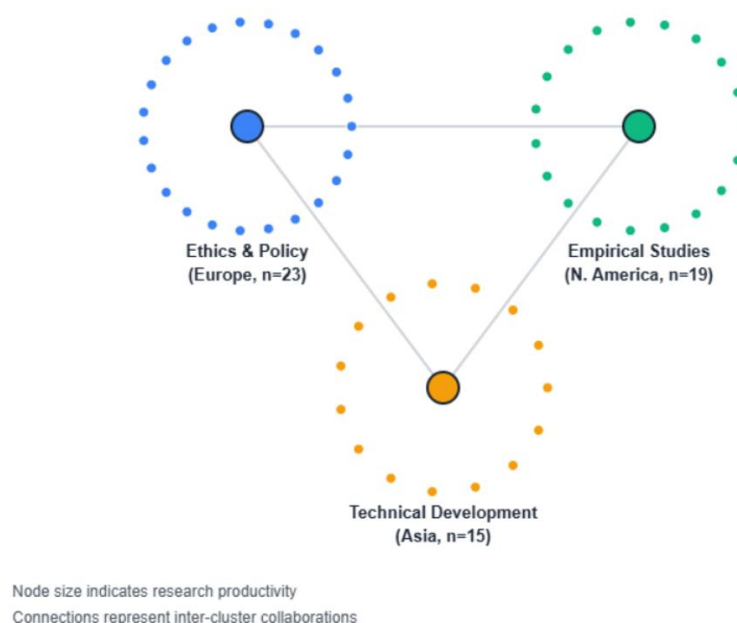


Figure 4. Co-authorship network analysis (schematic of the three main co-authorship clusters; cluster labels are researcher-assigned) (the authors' own elaboration)

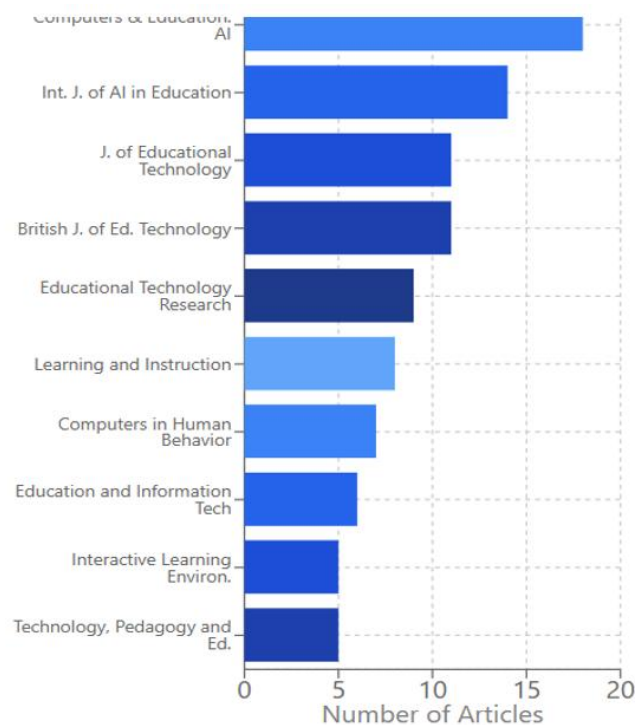
of the problems of GenAI in education. The regional labels attached to these clusters (European, North American, Asian) describe the predominant affiliations of the researchers in each cluster; VOSviewer grouped authors by collaboration links only, and the regional and thematic characterizations are descriptive interpretations made by the researchers.

The analysis of author keywords and research focus reveals that such collaborative clusters have various perspectives and ways. The themes of regulatory frameworks, data privacy, algorithmic bias, academic integrity, and European ethics cluster are frequent in European ethics cluster. North American empirical cluster pays attention to the regulated research of the educational consequences and profound comparisons of the AI assisted and traditional education and examination of student's attitude and perception of AI measures. Asian technical cluster is oriented on the design of systems, optimization of algorithms, applying natural language processing, and multimodal AI interfaces in education. These cluster-level characterizations are descriptive and tentative: clusters include authors from several countries, and the themes attributed to each reflect the most frequent keywords rather than the whole research agenda of any region.

High-Impact Journals and Publication Outlets

It can be seen in the diffusion of articles across sources of publication that there is a specific concentration in the number of featured journals that have emerged as the primary source of research regarding GenAI in education. The most popular in this research was the journal "Computers and Education: Artificial Intelligence" that had the most active activity (18 articles). The second-ranked journal was the International Journal of Artificial Intelligence in Education (14 articles), followed by the Journal of Educational Technology and Society and the British Journal of Educational Technology (11 articles each) (Figure 5). The similarities between these journals are a handful and can be likely traced down to their roles in publishing the research of GenAI in education. Firstly, they have established archives of the publication of high-quality research on the topic of educational technology and AI applications and thus are natural sources of researchers in this new field to publish their works. Second, their review times and publication timelines are fairly fast, which is also a major contributor to the dynamism of the GenAI technology that has become a rapidly evolving phenomenon. Third, certain of these journals have been prolific in soliciting submissions to special issues and calls to papers on GenAI, which is a sign of receptiveness to this study. These characteristics of the journals (review times, archives and special issues) were not measured in this study and are offered as tentative explanations.

Heavy percentages of the corpus were also occupied by the conference proceedings and 28 articles were published in such conferences as the International Conference on Artificial Intelligence in Education (AIED),



Note: Impact factors are approximate and based on 2024 journal metrics. Journal names have been abbreviated for display purposes.

Figure 5. Distribution of articles across leading journals (the authors' own elaboration)

Learning Analytics and Knowledge (LAK) Conference, and Computer-Supported Collaborative Learning (CSCL) Conference. The urgency and the speed of spreading the research on new technologies can also be outlined by the popularity of the conference publications.

Impact Factor Analysis

AI research generation in education is identified in high-impact journal outlets and the mean impact factor of journal corpus is 3.7 (as per 2024 metrics). This means that the research on the topic at hand is not pushed to low-end sources but rather regarded as a valuable research work which is supposed to be published in a highly esteemed journal. The leading sources (Figure 5) are predominantly education and educational technology journals, and the extent to which the topic also reaches multidisciplinary outlets was not examined in this study.

Distribution of Research Activity Area

Analysis of author affiliation suggests that there is a pattern of research distribution in the world with certain areas and nations being resounding on the research activity. The most productive in the study were the United States which had 42 articles (34.7 percent of the corpus), the United Kingdom with 24 articles (19.8 percent), China with 19 articles (15.7 percent) and Germany with 14 articles (11.6 percent). The presence of the articles by Australia (6-9), Canada (6-9), the Netherlands (6-9), and South Korea (6-9) may tentatively be associated with such factors as the availability of the developed AI infrastructure, the funding of the educational technology research, and the attempts to promote the AI innovation in education (Figure 6). These explanations are speculative: the bibliometric data document where publications are affiliated but not why output is concentrated in particular countries, and factors such as established research universities, public or private investment in AI, or supportive policy environments were not measured in this study and should be treated as tentative interpretations.

The differences in the scope and method of research are quite interesting, based on the regional trends. Empirical studies with respect to the outcome of student learning as well as the issues in practical

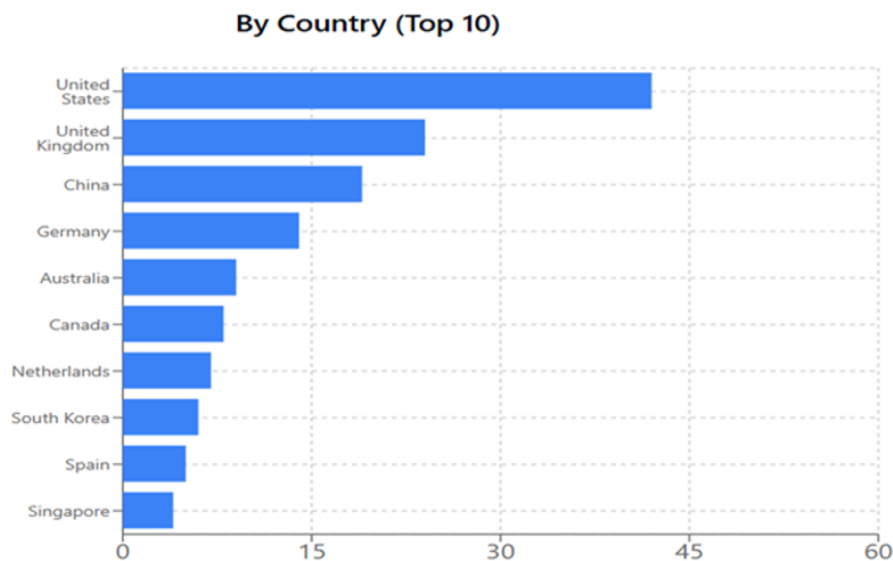


Figure 6. Distribution of publications by countries (the authors' own elaboration)

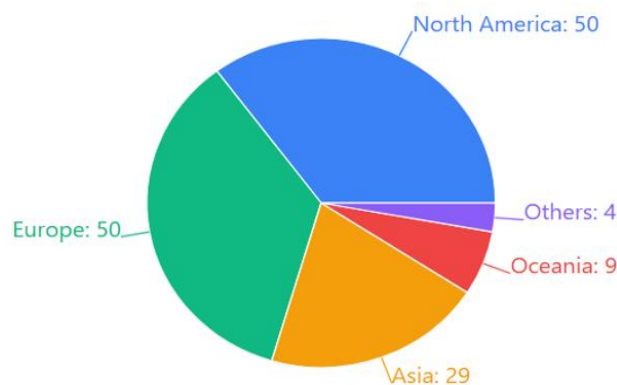


Figure 7. Distribution of geographic classification based on author affiliations (whole counting; the total of 142 exceeds 121 because articles with multi-country author teams are counted in each country) (the authors' own elaboration)

implementation appear to be more frequently emphasized in the North American-affiliated articles. European-affiliated articles appear to place more emphasis on ethical, social, and policy implications of GenAI in education, which may indicate, but does not demonstrate, that the region is actively engaged in AI regulation and digital rights. In the Asian-affiliated articles, technical development and system design appear strongly represented, which may be consistent with, but cannot confirm, the AI technology leadership of these countries. These regional contrasts are based on country-level counts and on the keyword profiles and affiliations of the co-authorship clusters; they describe tendencies within this Scopus-indexed, English-language corpus, were not statistically tested, and should be regarded as tentative interpretations.

The apparent under-representation of Latin American, African, and certain Asian nations may raise a concern about equity in the world both in terms of producing research as well as possibly accrued benefits as the product of GenAI uses in education (**Figure 7**). The trend may reflect differences in research funding, infrastructure, access to advanced AI technologies and language barriers in international publication; however, it may also be partly an artifact of this study's design, since the use of Scopus and the restriction to English-language documents are likely to under-represent research from these regions, and this could not be tested with the present data. The corrective actions to such imbalances are also of major concern to make sure that the research and development of the GenAI do not target that it aims to address the needs of well-resource regions in the world, but that of students across the world. **Figure 7** groups author affiliations into North America (50), Europe (50), Asia (29), Oceania (9) and Others (4); because "others" is not broken down, contributions from Latin America and Africa could not be quantified separately in this study.

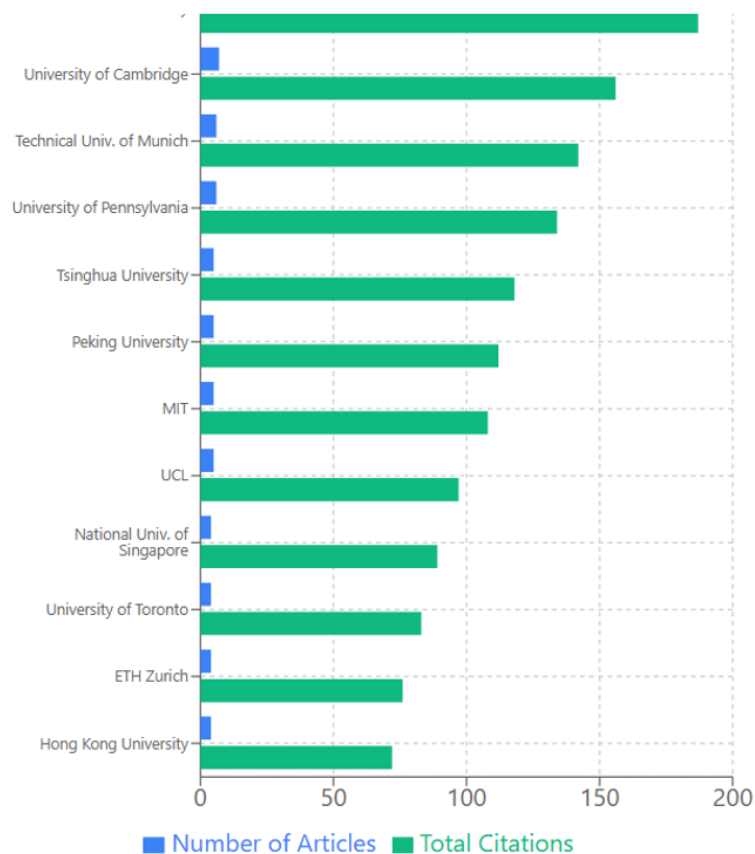


Figure 8. Leading institutions in GenAI education research (the authors' own elaboration)

Institutions and Sources of Finance

Investigation of institutional affiliations shows that the scholarly work on GenAI in education is spread across the various types of institutions, including research-based universities (comprehensive), technical (specialized), and education-oriented institutions. The most prolific organization was Stanford University with 8 publications, the University of Cambridge (7 publications), Technical University of Munich (6 publications) and the University of Pennsylvania (6 publications). These top institutions in China, such as Tsinghua University and Peking University, were also found to have an impressive amount of research output with 5 publications each (Figure 8). These institutions also have several features in common, which may plausibly contribute to their research output, although this was not examined in the present data. To begin with, they have robust computer science, and AI curricula, which offer technical skills required to study and research GenAI systems. Second, they have created education research centers or schools of education capable of bringing in pedagogical skills and educational background. Third, they usually possess institutional stakes in educational innovation and funding to make experimental uses of new technologies. These features are drawn from general knowledge of the institutions rather than from the bibliometric data and should be read as tentative.

The analysis of the source of funds, which can be found in 73 out of 121 articles, demonstrates a wide range of research in GenAI in education. The National Science Foundation (United States) was found to be the most often funder, with 18 articles, the Horizon Europe program of the European Commission (12 articles), the UK Research and Innovation councils (9 articles), and the National Natural Science Foundation of China (8 articles). It was also greatly assisted by the sources of private foundations and industry, with the Bill and Melinda Gates Foundation backing 6 articles and technology companies (mainly by providing unrestricted gifts of research) backing 11 articles (Figure 9). The prevalence of government sources may suggest the role of understanding and shaping the role of AI in education as a strategic matter by publicly managed agencies. It has been widely recognized that numerous government funding initiatives have placed a specific emphasis on studies in AI application and its potential impacts on society, and education is frequently cited as one of

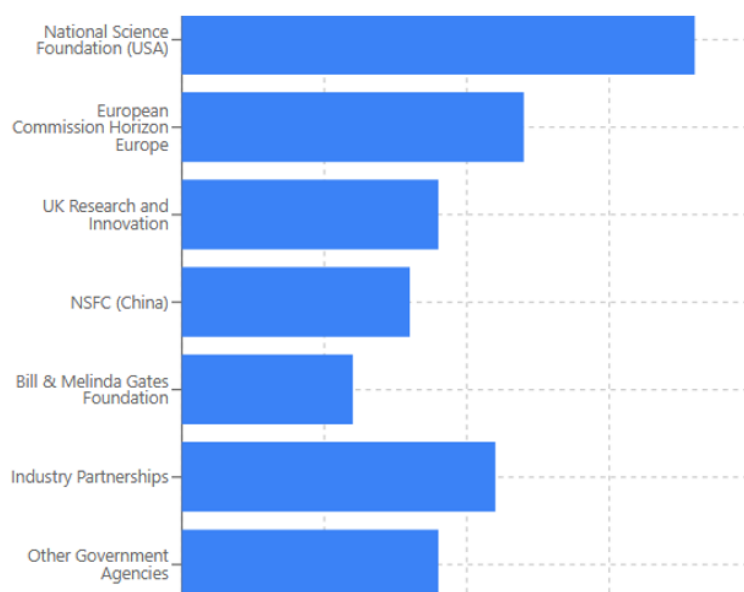


Figure 9. Distribution of funding sources (the authors' own elaboration)

those areas of interest. The presence of non-governmental sources of foundations and industry may indicate that these questions are of wider interest in society than is reflected by government sources and the relative amount of state funding to support the research questions may imply that this is more of a state-backed research agenda, however. Because funding information was available for only 73 of the 121 articles, these observations cover a subset of the corpus and should be interpreted cautiously.

Articles identified international support by a number of national agencies in 14 resulting in research partnerships with many countries. Such joint financial initiatives often supported comparative studies that used the application of GenAI to different education systems and cultural backgrounds that offered valuable data content on how contextual variables affected integration and success of AI.

Research Topics and Thematic Analysis

Thematic analysis of the GenAI in education literature corpus through thematic clustering and key word co-occurrence analysis showed that several important research topics were present. The clusters identified by VOSviewer served as the starting point; the thematic labels and the article-level counts reported below were assigned by the researchers, as described in the cluster formation and thematic labeling section, and because one article can belong to more than one theme, the percentages do not sum to 100%. The most apparent one that contains 67 articles (55.4%), is the theme of pedagogical uses and design of instruction, with GenAI tools. The cluster is interested in how educators could effectively introduce AI systems to the teaching process, develop learning activities, which could utilize AI opportunities and devise pedagogical frameworks, which could be deployed in the learning with AI.

The second theme that is important and which can be found in 54 articles (44.6%), is the issue of assessment and evaluation of GenAI. The paper touches upon the problems of academic integrity, designing systems of assessment that will be resistant to AI, using AI in automated grading and feedback, and changing the way assessment is conducted in order to prioritize the skills that are not competitive with AI but complementary to them. The popularity of the theme can be viewed as an indication of the general nervousness of teachers in relation to the concept of continuing to have effective and meaningful evaluation in the age of the forced introduction of AI technologies.

A third theme, which was checked and was found to be applicable, is of ethical and societal implications, and it was discussed in 48 articles (39.7%). Such risks as biasness in algorithms, information confidentiality, disparities in access, the likelihood of the emergence of educational distances through the assistance of AI, and training of moral principles and regulations of AI application to education will be discussed in the research. The overemphasis on ethical factors manifests the fact that the scholars consider the social and ethical implication of the technical skills.

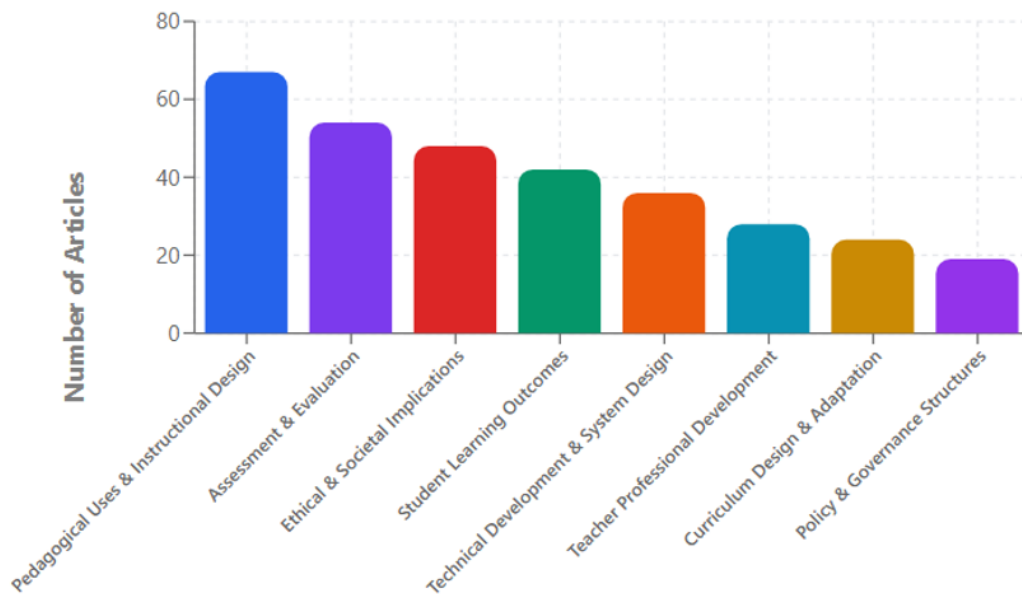


Figure 10. Distribution of research themes by article count (the authors' own elaboration)

The 34.7 percent of articles, i.e., 42 articles encompassed in this theme addresses the learning outcomes and experiences of the students. The empirical research studies would be used to examine how exposure to generative tool by the students influences student learning, student motivation, and student engagement whilst developing various competencies. Under this theme, the research has used controlled experiment, quasi-experimental research and qualitative studies examining student attitudes and experiences. The fifth major theme is technical development and system design that exists in 36 articles (29.8%). Its research findings are determined towards developing AI systems with orientation to the educational applications, increasing natural language processing in the educational conversations, developing multimodal AI component interfaces, and the overall adaptation of general-purpose AI models to the educational situations. Major but less eminent than pedagogical and ethical themes, technical research, is another important aspect of the literature.

The most populated areas of such representation would be professional development of teachers and AI literacy (28 articles), curriculum design and adaptation (24 articles) and policy and governance structures (19 articles). The variety of the themes is an indicator of the versatility of the implications of GenAI on the education and the extent to which such technologies are addressed by different researchers (Figure 10). The eight thematic labels, their scope and the number of articles assigned to each are summarized in Table 1.

The change in the research interests is denoted by time-thematic analysis. The initial literature (2023) was overrepresented with ethical and evaluation issues, anchored in anxieties of disruptive potential in GenAI, which took place early in its development. The more recent literature (2024-2025) indicates the change in the focus to the pedagogical integration and empirical research observations of the learning outcomes and depicts that the focus has at last shifted to the maturation of systematic research of the effective implementation strategies.

Influential Publications and Citation Analysis

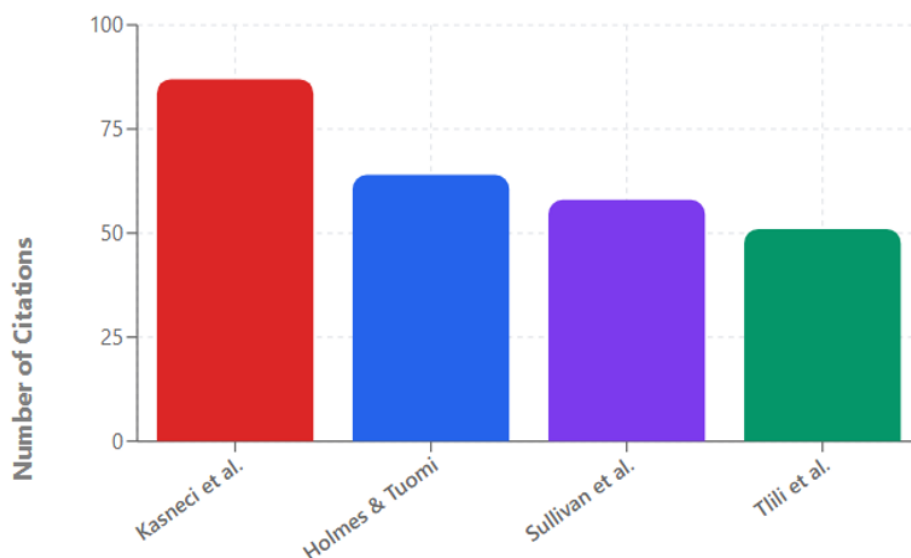
Citation analysis recognizes the most significant publications in the corpus and uncovers the knowledge constitution and intellectual impact trends. The article that was cited most, was "ChatGPT for good? On opportunities and challenges of LLMs for education" by Kasneci et al. (2023), which received 87 citations throughout the study period, which provides background views on the opportunities as well as threats of LLMs in education. The outstanding effect of this article is due to its timeliness during the period of publication, scope, and balanced approach to the opportunities and concerns.

Various other publications had significant citation effect even though most of them are recent. The article by Holmes and Tuomi (2023) titled "State of the art and practice in AI in education" received 64 citations, and

Table 1. Researcher-assigned thematic labels, their scope, and the number of articles assigned to each

Thematic label (researcher-assigned)	Scope (based on keywords and article content)	Articles: n (%)
Pedagogical uses and instructional design	Integration of GenAI into teaching, design of learning activities and pedagogical frameworks	67 (55.4)
Assessment and evaluation	Academic integrity, AI-resistant assessment design, automated grading and feedback	54 (44.6)
Ethical and societal implications	Algorithmic bias, data privacy, unequal access, moral principles and regulation	48 (39.7)
Student learning outcomes	Effects on learning, motivation and engagement; student attitudes and experiences	42 (34.7)
Technical development and system design	Educational AI systems, natural language processing in educational dialogue, multimodal interfaces, adaptation of general-purpose models	36 (29.8)

Top 4 most cited publications in the corpus

**Figure 11.** Most influential publications by citation count (the authors' own elaboration)

it offers systematic studies of how AI has the potential to change many different areas of education. The article "ChatGPT in higher education: Considerations for academic integrity and student learning" by Sullivan et al. (2023) had 58 citations, discussing implications for academic integrity and student learning. The article by Tiili et al. (2023) entitled "What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education" was cited 51 times, which is an indication of high demand in normative frameworks applied to AI implementation (Figure 11).

The co-citation analysis and identification of publications led to the establishment of intellectual relationships between publications and finding publications that were cited together and possibly on the same conceptual basis or complementary viewpoints. The co-citation cluster with the most links is between the publications on the ethical frameworks, the policy development and the equity. It shows the fact that researchers exploring these issues rely on similar background publications. The second co-citation cluster relates empirical research of learning outcomes and hints at the evolving evidence base on which the study builds up the comparative and the replication research.

It was found that the study on GenAI in education is founded on numerous intellectual traditions when analyzed in a reference list. It is not unique that the learning sciences, educational psychology, and instructional design have works at their foundations, and it implies that such attempts should anchor AI applications based on the established educational theory. Technical background is provided by standard publications in AI and machine learning, but normative views are provided by the recent literature on AI ethics and an algorithmic fairness. This interdisciplinary citation format reflects the complicated nature of the questions connected to the GenAI in education.

The relatively large number of citations (citations per year) in the recent publications is an indication of a very recent surge in knowledge and construction of the current work. The number of 2024 publications already counted a number of citations above the vast majority of publications in 2023, which is an indication of a faster rate of research and attention to new discoveries. This tendency shows that this is an active and high-paced sphere where the input into the field will be incorporated into the existing body of research within a short period.

DISCUSSION

Bibliometric analysis as done in this study demonstrates that the research field in question is rapidly developing with significant growth, global cooperation and changing thematic priorities. The fact that the number of publications has grown exponentially from 2023 till 2024 and the activity continues until 2025 shows that scholars are highly engaged in exploring the implications of GenAI in education. This trend appears to outstrip general educational technology research growth (a comparison not tested in this study), which may imply that GenAI is a discontinuous innovation, which must be addressed by researchers urgently, and not a gradual technological innovation, which can be studied over time.

The institutional and geographical spread of research activity demonstrates the opportunities and threats of promising global activity. Although the significant role of North America, Europe, and Asia, in the development of GenAI demonstrates its global acknowledgment of the importance of education to researchers, the comparative lack of Latin American, African, and other parts of Asian research, begs significant questions regarding the perspectives and priorities of which researchers are driving the development of this new domain. These questions should be considered tentative, because the apparent under-representation may partly reflect Scopus indexing and the English-language restriction rather than an absence of research. Since it can be expected that GenAI systems will become widespread throughout the world, there will be a need to make sure that different voices are reflected in the research discussion, which is not only an equity issue but also a practical need to create methods that can meet diverse educational settings, cultural priorities, and social demands.

The fact that the studies are accentuated in the well-resource-based institutions in the more economically developed regions may point to, although this study cannot confirm, disparities in research infrastructure and unequal access to the subsequent AI applications and expertise that will be necessary to provide the said research. The risk of this trend is that the regions that have already led the pack in regards to the level of technological advancement will gain. The same dilemma can only be addressed through conscious attempts to build capacity for research, development of international relationships that can effectively empower the researchers in the underrepresented regions as well as ensuring that funding systems are made to invite all geographies to join.

Based on the thematic analysis, it suggests that it is a discipline that not only has difficulties with the technical possibilities and pedagogical alterations but also with the ethical implications. It is not surprising that the assessment and the problem of academic integrity is the source of publications in the early days due to the fear of a situation when GenAI breaks down the developed assessment processes. However, the greater focus of the new publishes on pedagogical integration and the learning outcomes of more recent articles shows that the reactive issue of learning technologies can be fruitfully replaced by the active exploration of how the learning processes can be adjusted to the exploitation of AI opportunities without the decline of the educational process and quality of it.

It has been observed that the ethical nature of the studies that have been conducted on the concept of GenAI in the educational sector receive considerably broad attention and importance than other spheres of AI implementation, where the ethical consideration acquires a secondary stress and importance in comparison with the technical functionality and business opportunities. Such attention is likely to reflect the professional needs of teachers to consider student welfare and educational justice, and publicity of learning institutions that puts accountability strains. The diversity of ethical considerations discussed in the article, including algorithmic bias, data privacy, academic integrity, and equity of access, is a sign of complex thought on which ethical use of GenAI presupposes taking many factors of its potential harm or usefulness into consideration.

The collaborative networks that are determined through co-authorship analysis reflect the formation of research communities that are created due to shared interests and complementary knowledge. The existence of separate clusters on ethical frameworks, empirical results and technical development refer to the productive specialization and the connections between clusters indicates major cross-fertilization of ideas. Such a great contribution to global collaboration observed (out of every three articles, more than one-third of articles featured multi-country author teams), may tentatively be explained by the view that GenAI in instruction is a global challenge, which must be addressed by collaboratively creating knowledge in the country settings.

Nevertheless, the dynamics of cooperation also aggregate the fact of the possibility of insularity as only 34% of the articles involved authors from more than one country, although the present data do not allow us to conclude whether collaborations occur mainly within regions. More intensive building of connections between European, North American, and Asian research communities and broadening the interaction with researchers in areas to date underrepresented can further broaden the potential of developing insights that are useful to be deployed in different contexts. This would be especially useful since partnerships would be selectively engaged in the comparative analysis of the implication of GenAI to the field of education and the most efficient variations of its integration.

The environment of funding of the research area suggests, for the 73 articles that report funding, that the source of most known funding of the research area is the governments which provide the funding of the research in the field of education. The presence of this trend may imply that the implication of AI as an educational good of the people is apprehended by the corresponding type of common funders to be an investment. The fact that a notable share of the research (11 of the 73 funded articles) has been funded by industry sources, however, does leave the question whether the research priorities and interpretation can be influenced or not. Even though the connection to the industry could prove a valuable resource base and experience-based comprehension, the crucial independence will be promoted especially when one is to pursue a research study on the possible harm or constraint of commercially designed AI systems.

The chronologic change in the topic of study reveals that a subject matter has left the phase of basic anxiety and formation of thoughts to a phase of systematic research into the topic and the theoretical recommendation on how to implement the issue. The first publications were inclined to discuss what questions, in other words, what does GenAI do, what can be used to do, what the potential implications are, what are the ethical considerations. More up-to-date sources are more concerned with questions, and how can AI be incorporated into the practice of pedagogy, how students learn with the help of AI resources, and how the practices of assessment may be modified. The success of this development is the indicative signal of the sound field development, yet much remains to be accomplished to come up with the evidence-based recommendations to the practitioners and policymakers.

The reference formats are reflective of knowledge accumulation of high intensity because high-profile primal editions are shortly to stand as sources of future publications. The citation velocities of the publications that are not old are high enough to presume the active interest in the new findings as opposed to using only the seminal publications of the past. However, the large number of citations with a relatively small amount of highly cited articles could be an element that demonstrates the presence of an echo chamber, where one of the perspectives and a result are disproportionately featured in comparison to others. Methodological and conceptual diversity is to be promoted to be able to have a solid knowledge development.

It is this bibliometric study that reveals the limitations of the available studies. Firstly, although 42 articles (34.7%) address student learning outcomes and experiences, this bibliometric study did not appraise study design or quality, so the strength of the evidence available for practice cannot be judged here. Even though the conceptual work is particularly well suited at the initial stages of the field formation, the need to employ strict empirical study increases during decisions of making choices on implementation as the institutions begin to take them. Second, the literature on different sets of learners, the educational levels as well as their disciplines is not comprehensive and the focus on the higher education and certain disciplines is not appropriate. More diverse studies are required to gain a better understanding of the various educational implications of the GenAI usage under different circumstances.

Third, there appear to be few longitudinal studies (study design was not coded in this analysis) focusing on the long-term effect of introducing AI on learning, teaching, and the functioning of the institution, which, of course, restricts the scope of research of the field, but will fill the gap at the right time when such studies will become feasible. Fourth, the researchers specifically addressing the equity, access, and whether AI can increase disparities of education have not been conducted to a sufficient extent regarding the relevance of the questions. Although the ethical concerns are provided with a substantial portion of the discussion in the abstract, a more empirical investigation on the effect of the GenAI on various student positions and communities should be strengthened. Fifth, professional growth, process pedagogies, and institutional implementation issues are not as widely reported in comparison with technical skills and student applications; however, the given type of research is highly necessary in the success of the successful implementation of AI.

CONCLUSION AND IMPLICATIONS

The bibliometric analysis may demonstrate the GenAI in education as a fast-growing area with booming publication rates, impressive international cooperation, and dynamic thematic focus. The development of initial caution on disruptive potential to systematic examination of pedagogical integration and learning outcomes may indicate good field development, although much effort will still be required to formulate evidence-based practice and policy advice. The apparent prevalence of research from economically developed areas in this Scopus-indexed, English-language corpus, which should be interpreted tentatively, poses some significant questions regarding whose viewpoints this new area is oriented towards and how to make sure that GenAI represents a wide range of educational needs of various people of the world in an equal manner.

Author contributions: **LYL:** conceptualization, investigation, methodology, writing – original draft; **OC:** conceptualization, supervision, validation, writing – review & editing; **VGG:** data curation, investigation, methodology, writing – original draft; **SPZ:** resources, validation, writing – review & editing; **VLZ:** data curation, investigation, writing – original draft; **LMS:** visualization, writing – review & editing. All authors approved the final version of the article.

Funding: The authors received no financial support for the research and/or authorship of this article.

Ethics declaration: The authors stated that this study did not require ethics committee approval since it is based on articles already in the existing literature.

AI statement: The authors used AI-based tools just for language editing and grammar checking during the preparation of this manuscript. The whole scientific content, data interpretation and conclusions are the sole responsibility of the authors.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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