International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 6, December 2026, pp. 4726~4742
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i6.38937

A bibliometric performance analysis of generative artificial intelligence in higher education

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Article Info

Article history:

Received Feb 2, 2026
Revised Jun 29, 2026
Accepted Aug 6, 2026

Keywords:

Bibliometric analysis
Educational technology
Generative artificial intelligence
Higher education
Research productivity

ABSTRACT

Generative artificial intelligence (GenAI), particularly ChatGPT (November 2022), has profoundly transformed higher education, yet the current research landscape remains fragmented and insufficiently mapped. Although prior bibliometric and systematic reviews have addressed AI in education broadly or across all educational levels, none has concentrated specifically on GenAI in higher education during the post-ChatGPT period through three complementary analytical dimensions. To address the gap, a bibliometric performance analysis was conducted on 306 articles indexed in the Web of Science (WoS) core collection up to 31 October 2025, following preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines and examining productivity, citation impact, and thematic composition. Results showed rapid growth from 12 articles in 2023 to 191 in 2025, involving 979 authors and 253 institutions across 67 countries, led by China, the United States, and England, accruing 3,646 citations concentrated in foundational works on student perceptions and academic integrity across 30 research areas. Thus, the present study contributes a dedicated three-dimensional bibliometric performance map of post-ChatGPT GenAI research in higher education, integrating productivity, citation impact, and thematic composition, and offering academicians, policymakers, and practitioners an evidence-based foundation for more effective engagement with the current rapidly expanding field.

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1. INTRODUCTION

With the introduction of generative artificial intelligence (GenAI), particularly ChatGPT, to the public in November 2022, there have been profound transformations in the academic discourse on existing teaching and learning approaches used in higher education [1]. As different large language models (LLMs) can generate human-like text, create codes, and engage in sophisticated dialogues, there has been the emergence of educational innovations, accompanied by concerns related to critical thinking, academic integrity, and the boundaries on the assistance offered to students [2], extending longer-standing debates on AI in higher education [3]. Within several months of the public introduction of ChatGPT, different higher educational institutions (HEIs) worldwide enacted corresponding policies, ranging from complete prohibition to vigilant use [4], and educators acknowledged that conventional approaches of student evaluation could be ineffective when students used AI tools to produce more advanced written work [5]. As such, the current discourse is concentrated on the balance between opportunity and risk.

In response to the developments, academicians have exhibited proactive actions, as indicated by a rapidly expanding knowledge body that concentrated on student perceptions of GenAI, the adoption of GenAI technologies across different fields, the redesign of student evaluation, and the policymaking processes of HEIs [6]. Nevertheless, the rapidly expanding body of knowledge has rendered the current intellectual structures of the field difficult to pinpoint in terms of contributions and future directions. Although conventional methods, including narrative reviews, can be instrumental in synthesizing different research themes, they might not be suitable for accurately capturing the magnitude and breadth of the intricate research landscape mapped by earlier systematic reviews [7]. Comparatively, a more rigorous method will be the bibliometric analysis, which can map intellectual structures [8], document developmental pathways and foundational studies, and reveal geographical or institutional centers of research in rapidly proliferating fields [9].

Despite the growing body of knowledge, three specific research gaps have remained. First, prior bibliometric and systematic reviews have addressed broader scope only, including Zawacki-Richter *et al.* [7] and Crompton and Burke [3] on AI in higher education generally, Bond *et al.* [10] on AI in higher education through a meta-review of prior systematic reviews, and Bahroun *et al.* [11] on GenAI across all educational sectors. Two more recent works have begun to address segments of the scope; Frumin *et al.* [12], who mapped GenAI research in higher education between 2022 and 2024; and Anthony and Sharma [13], who examined the bibliometric trajectory of ethics in AI for academic research. However, the previous works either covered a shorter window without an explicit three-dimensional analytical structure or addressed a different topical scope (academic ethics rather than higher education in general). Second, none of the works has concentrated specifically on GenAI in higher education during the post-ChatGPT period, despite the unique considerations of higher education, namely higher degrees of academic autonomy, closer integration of research and teaching, greater complexity in student evaluation, and more extensive responsibilities for professional development [14], [15]. Third, to our knowledge, no prior review has examined the field through three complementary dimensions, namely, research productivity, citation impact, and thematic composition.

To address the gaps, in the present study, one overarching scientific question is investigated, namely, what are the patterns of research productivity, citation impact, and thematic composition of research on GenAI in higher education between 2023 and 2025, and how do the patterns reveal the intellectual structure and maturation of the current rapidly emerging field. Specifically, three corresponding research questions (RQs) are formulated, each paired with a matching research objective (RO). The first research question (RQ1) examines the landscape of research productivity in terms of annual publication trends, leading authors, HEIs, countries or regions, and publication sources, and the first research objective (RO1) is to identify the top 10 most productive authors, HEIs, countries or regions, and journals. The second research question (RQ2) investigates the academic influence of the field through annual citation trends and the most cited articles, and the second research objective (RO2) is to identify the top 10 most cited articles. The third research question (RQ3) addresses the multidisciplinary composition of the field, and the third research objective (RO3) is to identify the top 10 Web of Science (WoS) research areas. Through the investigation, the present study contributes a dedicated three-dimensional bibliometric performance map of post-ChatGPT research on GenAI in higher education, integrating productivity, citation impact, and thematic composition, which offers academicians, practitioners, and policymakers an evidence-based foundation for more effective engagement with the current rapidly expanding field.

2. METHOD

In the present study, the bibliometric analysis was conducted to have a systematic evaluation of the current landscape of GenAI research in higher education, as the method could be considered a more rigorous quantitative technique for examining the existing body of knowledge regarding the patterns of publications, the dynamics of citations, and the distributions of research themes [8]. Hence, the present study could map existing intellectual structures, determine influential authors, and reveal the latest developmental trends in specific research areas, especially for rapidly proliferating fields, including GenAI research in education [9]. The analysis was conducted by adhering to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines, as depicted in Figure 1.

2.1. Database selection and search strategy

As the exclusive data source, the WoS Core Collection was chosen in the present study owing to its rigorous standards of indexing, holistic coverage of high-impact journals, and high degrees of acceptance in bibliometric research [16]. Specifically, three complementary considerations supported the selection. First, the WoS Core Collection enforces selective journal inclusion criteria that prioritize editorial quality and peer-review rigor, which contributed to a more reliable foundation for analyzing established academic discourse [16]. Second, the WoS Core Collection offers structured citation indexing and standardized metadata fields,

namely, authors, affiliations, abstracts, keywords, and cited references, which underpin the science-mapping tools widely used in bibliometric analysis and supported the productivity, impact, and thematic analyses conducted in the present study [17]. Third, influential prior reviews of AI and GenAI in education have relied on major citation databases [3], [7], [11], which variously drew on WoS, Scopus, and additional databases; grounding the present analysis in the WoS Core Collection therefore situates its results within this established body of work.

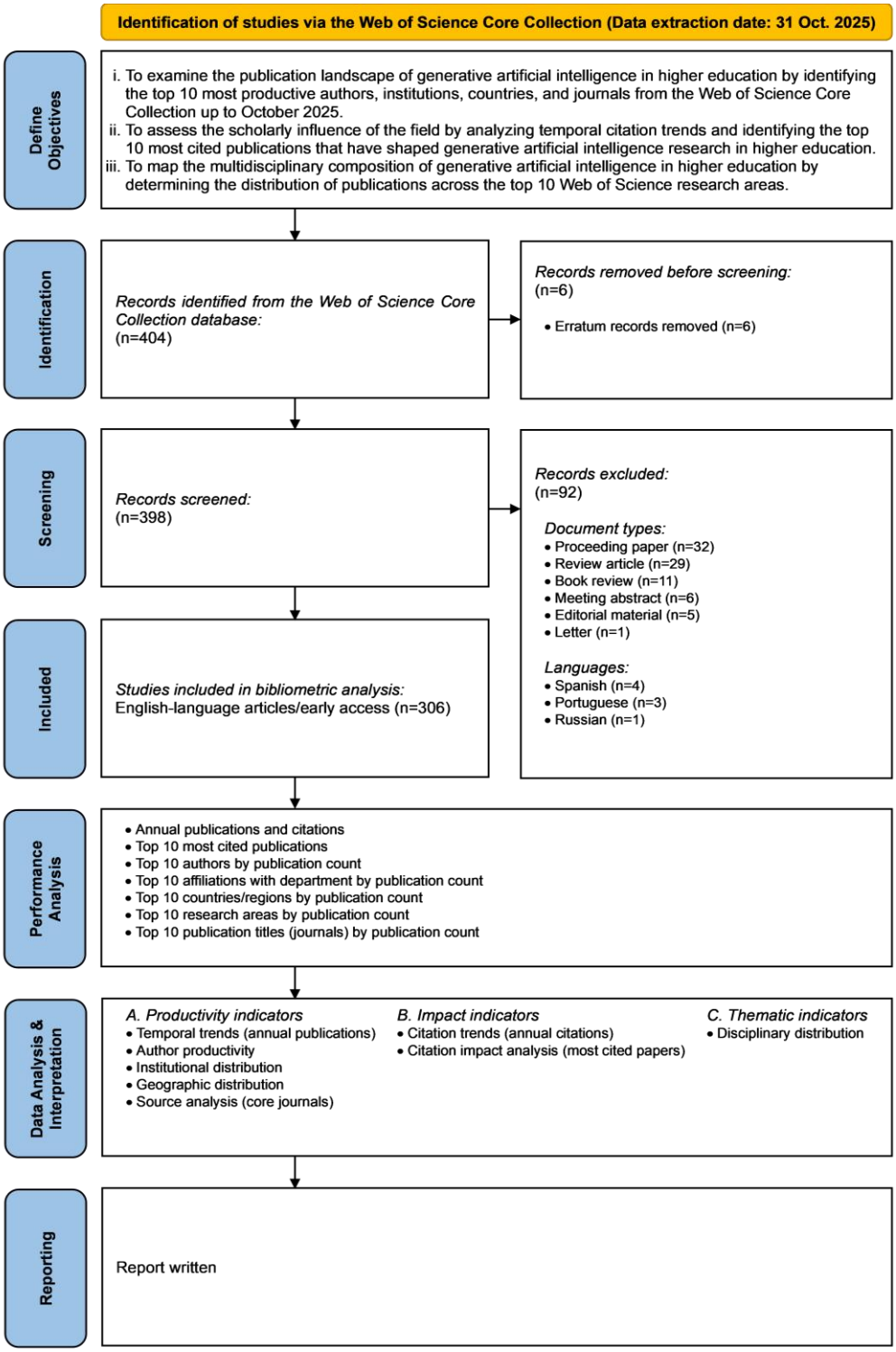


Figure 1. PRISMA-based bibliometric analysis methodology [18], [19]

The approach is also consistent with established bibliometric practice across diverse disciplines, as demonstrated by recent WoS-based bibliometric analyses on postoperative pain and nursing [20], International Financial Reporting Standards (IFRS) adoption in Africa [21], and the application of social media in supply chains [22], all of which adopted the WoS Core Collection as the exclusive data source. Although Scopus and other databases offer broader journal coverage, the use of the WoS Core Collection inevitably introduced a database-coverage bias, in which articles indexed only in other databases were excluded from the present sample. Thus, the present results are best interpreted as describing the WoS-indexed segment of the current research field, and the above-mentioned bias is acknowledged alongside the other limitations of the study. The process of data extraction commenced on 31 October 2025, with all available articles collected up to that date using Boolean operators and field-specific tags in the search strategy, which could guarantee high levels of accuracy and comprehensiveness. The search query targeted document titles through the following terms: TI=("generative artificial intelligence" OR "GenAI" OR "genai" OR "gen-ai" OR "gen ai" OR "gai") AND TI=("higher education*" OR "higher learning" OR "post-secondary education*" OR "postsecondary education*" OR "tertiary education*" OR "universit*" OR "college*"), guaranteeing that all extracted articles focused on the dynamics of GenAI adoption in higher education.

2.2. Sampling method

In the present study, a purposive, criterion-based sampling approach was adopted, which was applied to the full population of articles that met the eligibility criteria within the WoS Core Collection, instead of a probability-based sample drawn from a larger pool [8]. The approach was widely adopted in bibliometric research, as the objective of the present study was to map the complete intellectual landscape of the defined research field rather than to generalize from a subset to a broader population [8], [23]. Specifically, the sampling frame was established according to three complementary parameters, namely, the data source, which was restricted to the WoS Core Collection owing to its rigorous standards of indexing and high degrees of acceptance in bibliometric analysis [18]; the observation window, which extended from 1 January 2023 to the extraction date of 31 October 2025, corresponding to the period immediately following the public introduction of ChatGPT in November 2022 and capturing the early-stage development of the current field, and which included one article that was indexed within this window but carries a WoS publication year of 2026; and the topical scope, which was defined by the title-field (TI) Boolean query pairing GenAI terms with higher-education terms. All articles identified within the sampling frame were retained for further screening by applying the PRISMA-based inclusion and exclusion criteria. Thus, the final sample of 306 articles represents a census of WoS-indexed English-language original and early access articles on GenAI in higher education during the period of observation, rather than a statistical sample. As such, the sampling strategy supports the analytical objective of mapping the structural and intellectual composition of the current rapidly emerging field in a comprehensive and transparent manner [9].

2.3. Selection criteria and PRISMA framework

The PRISMA guidelines were adhered to during the analysis, as the guidelines could guarantee higher degrees of methodological transparency and reproducibility [16], [17]. Through the initial search, there were 404 articles collected from the WoS Core Collection. According to the optimal practices, each of the extracted articles was manually validated to ensure high data quality and accurate results [19], which determined and eliminated six erratum articles, with the remaining 398 articles retained, consistent with the data-cleaning practice adopted in prior bibliometric studies [24]. Subsequently, both the stipulated inclusion and exclusion criteria were applied to refine the dataset in the screening stage. Only original and early access articles were retained, as they represented primary contributions to the existing literature, with a total of 84 articles excluded, namely, proceeding papers (n=32), review articles (n=29), book reviews (n=11), meeting abstracts (n=6), editorial materials (n=5), and letters (n=1).

Apart from the article-type criteria, the language criterion was applied to retain only English-language publications, which removed eight articles published in Spanish (n=4), Portuguese (n=3), and Russian (n=1). Three complementary considerations supported the decision. First, English is the dominant language of international academic publishing in the WoS Core Collection, particularly in the educational technology and higher education research areas, wherein non-English contributions form a smaller proportion of the indexed output [18]. Second, the bibliometric indicators applied in the present study, namely citation counts, h-indices, and average citations per article, are most reliably comparable across articles published in the same language, as multilingual datasets can be subject to citation patterns shaped by linguistic communities rather than substantive contributions. Third, the application of the language criterion supported analytical consistency in the keyword-based thematic mapping, in which non-English titles, abstracts, and keywords would have required translation procedures that could potentially introduce additional sources of variation. In addition, the combination of original and early access article types with English-only inclusion is consistent with established bibliometric practice, as adopted by Bozkul and Uğraş [20] in postoperative

pain and nursing research, by Effah [21] in IFRS adoption research, and by Hoang *et al.* [22] in supply chain research, all of which applied identical article-type and language criteria within WoS-based investigations. Although the considerations supported the present approach, the use of English-only articles inevitably introduced a linguistic bias, wherein valuable contributions from non-Anglophone regions, including Latin America, parts of Asia, and parts of Europe, where research on GenAI in higher education is also actively advancing, were excluded from the present sample. As such, the present results are best interpreted as reflecting the English-language segment of the WoS-indexed research field, and the above-mentioned bias is acknowledged alongside the other limitations of the study. Resultantly, a total of 306 English and early access articles were retained for the bibliometric analysis.

2.4. Analytical framework

In the performance analysis framework, the dataset was divided into three complementary groups of indicators, in line with the ROs and with standard bibliometric performance-analysis procedures [25]. In particular, productivity indicators examined the distribution of research outputs across institutional, authorial, temporal, geographical, and source dimensions, namely, annual publication trends, the top 10 most productive authors, HEI contributions with departmental affiliations, geographical distributions across nations or regions, and journals as the main publication sources. Meanwhile, impact indicators investigated the academic impact in terms of citation metrics [26], [27], which included the analysis of the temporal citation trend to uncover annual citation patterns and the top 10 most cited articles that served as the foundational works of the intellectual development of the field. Consequently, articles with profound academic impacts within the research community were determined. In addition, thematic indicators appraised the composition of the research areas by mapping different articles based on the WoS subject categorization system, which, despite documented limitations such as ambiguous multi-category assignments, has served as a widely used basis for bibliometric subject mapping [28], in which the top 10 research areas were identified through the publication count. Accordingly, the thematic dimension reported here provides a category-level rather than a fine-grained, keyword-derived map of the field.

2.5. Data analysis procedures

The bibliometric data were extracted from WoS in tab-delimited format and processed on Microsoft Excel for descriptive analysis, with publication and citation metrics computed for each aspect, namely counts, percentages, average citations per item, total citations, and h-index values [29]. These indicators are reported under the column abbreviations publication year of the first article (PYS), number of publications (NP), sum of times cited (STC), average citations per item, equal to STC divided by NP (AC/I), and the h-index, while the other reports the article title, the author(s) and reference (Source), the publication title (PT), and the times cited (TC). The procedures were carried out by following established bibliometric protocols, which guaranteed sufficient replicability and methodological rigor [23], [30]. In addition, all derived metrics were independently cross-checked against the WoS-generated summary records to ensure that the productivity, impact, and thematic indicators were consistent with the underlying source data. In the ranking tables, entries with equal publication or citation counts are presented in the order provided by the WoS analysis. Country and region names follow the WoS country/region metadata, with minor standardization of label formatting for readability. WoS records England, Wales, and Scotland as separate units rather than aggregating them into the United Kingdom. Hong Kong SAR, however, is not recorded as a separate country/region in this field; addresses in Hong Kong are recorded by WoS under China (Peoples R China) and are therefore included within the China count. The institution-level label “Hong Kong SAR” used in this study reflects the affiliation address rather than a separate country unit.

Two analytical bases are used in section 3. All productivity, impact, and thematic indicators other than the annual publication trend, including Tables 1 to 6 and all citation totals, are computed on the full dataset of 306 articles. The annual publication trend in Figure 2 is computed on the 305 articles with a WoS publication year of 2023, 2024, or 2025. The remaining article met every eligibility criterion and was retrieved at the 31 October 2025 extraction but carries a WoS publication year of 2026. It is therefore retained in the full dataset but not plotted as a separate publication year, as a single record with a 2026 publication year cannot represent annual output for a year outside the observation window. The annual citation series in Figure 2 reports citations received in each calendar year by all 306 articles and is unaffected by this distinction. Values for 2025 cover the period up to 31 October 2025.

3. RESULTS

In this section, the results obtained from the bibliometric analysis of the final dataset of 306 articles on GenAI in higher education, indexed in the WoS Core Collection up to 31 October 2025, are reported.

The synthesized results were categorized into three complementary aspects, namely, the patterns of research productivity in terms of publication trends, leading contributors, and journal distributions, the citation impact analysis that identified the academic impact and foundational works, and the thematic analysis that mapped the composition across 30 research areas. Collectively, the present results established the structural and intellectual landscape of the rapidly expanding field.

3.1. Productivity analysis

The productivity patterns of research on GenAI in higher education were revealed through five complementary aspects, namely annual publication trends between 2023 and 2025, the leading 979 authors and 253 institutional affiliations, geographical distributions across 67 countries or regions, and the distributions of journals across 157 publication sources. The five aspects collectively form the structural fundamentals of academic outputs in the current field. Each of the aspects is examined in turn in the following subsections.

3.1.1. Annual publication trends

The temporal distribution of articles, as portrayed in Figure 2, demonstrated an intensive proliferation between 2023 and 2025 in tandem with the public introduction of ChatGPT in November 2022 [31]. Specifically, there was a growth from only 12 articles in 2023, when scholars began conceptualizing the new technological disruption, to 102 articles in 2024 and 191 articles in 2025, representing approximately 16-fold growth across the three publication years. These 305 articles form the basis of the annual trend, while the one remaining article in the full dataset of 306, which carries a WoS publication year of 2026, is not plotted as a separate year but is retained in all other analyses. The trend reflected the rapid responsiveness of academicians to GenAI in education and the intensive expansion of the research field within a short observation window. The 2025 count covers records retrieved up to 31 October 2025.

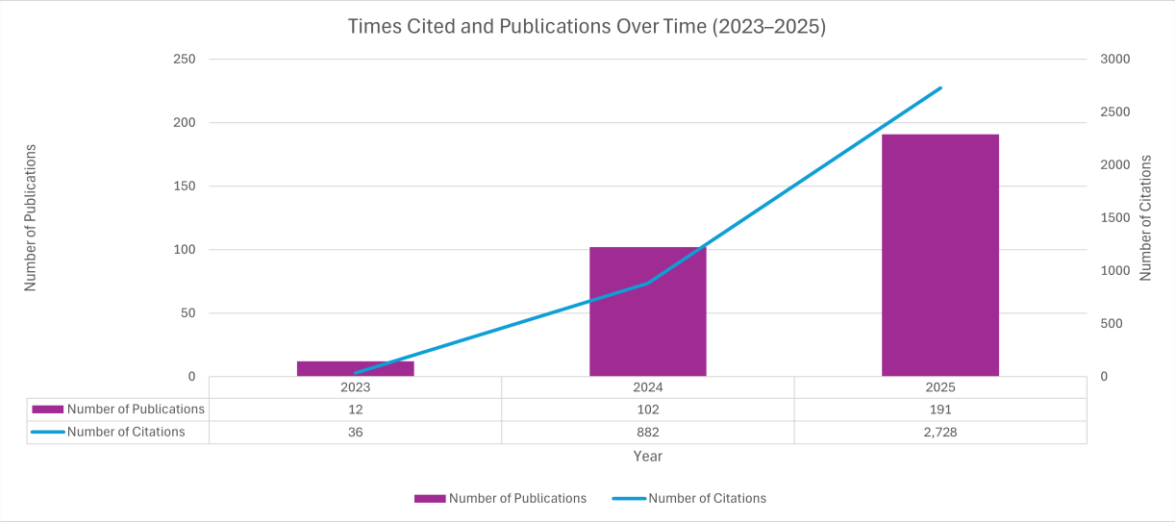


Figure 2. Annual publications by WoS publication year, 2023 to 2025 (n=305), and citations received per calendar year by all 306 articles, with 2025 values up to 31 October 2025

3.1.2. Top 10 authors by publication count

As indicated in Table 1, the level of author productivity reflected a highly fragmented landscape, wherein the 10 most prolific authors each contributed three or two articles only, with no individual author exceeding 0.98% of the total dataset. In total, there were 979 unique authors across 306 articles, translating into an author-to-publication ratio of approximately 3.2:1, which highlighted that no prominent author has yet emerged in the current rapidly expanding field. Although the productivity counts among the top 10 were broadly comparable, the citation impact varied substantially, wherein Shahzad and Xu attained the largest number of citations (99 each across three articles), followed by Khlaif (44 citations across three articles), and based on each author's primary affiliation, the top 10 authors were distributed across five countries or regions, namely China, Pakistan, Russia, Spain, and Palestine, with two authors also holding secondary affiliations in Singapore and Oman.

Table 1. Data summary of the top 10 authors (source: WoS)

Rank	Author	PYS	NP	STC	AC/I	h-index	Country/region
1	Baloch FA	2025	3	2	0.67	1	Pakistan
2	Bannister P	2024	3	23	7.67	3	Spain
3	Jaffar M	2025	3	2	0.67	1	Pakistan
4	Jogezai NA	2025	3	0	0.00	0	Russia
5	Khlaif ZN	2024	3	44	14.67	2	Palestine
6	Li Y	2025	3	1	0.33	1	China
7	Shahzad MF	2025	3	99	33.00	3	China
8	Wang J	2025	3	1	0.33	1	China
9	Xu S	2025	3	99	33.00	3	China
10	Asad MM	2024	2	9	4.50	1	Pakistan

3.1.3. Top 10 affiliations with the department by publication count

As shown in Table 2, the University of Hong Kong Faculty of Education was the most prolific institutional unit, as reflected by six articles, followed by five units with four articles each and four units with three articles each. The total of 253 unique departmental affiliations across reporting institutions further reflected a highly fragmented institutional landscape, although Hong Kong-based units accounted for six of the top 10, which may indicate its emergence as a prolific academic hub for research on GenAI in education. As department-level affiliation data were reported for only 132 of the 306 records (43.1%), this institutional analysis describes the reporting subset rather than the full corpus, and the unreported 56.9% may not be evenly distributed across regions. Furthermore, the citation performance varied within the top 10, wherein Beijing University of Technology's College of Economics and Management attained 99 citations and an h-index of 3 from only three articles, exceeding the larger-output University of Hong Kong Faculty of Education (71 citations across six articles) on a per-article basis.

Table 2. Data summary of the top 10 affiliations with the department (source: WoS)

Rank	Affiliations with the department	PYS	NP	STC	AC/I	h-index	Country/Region
1	The University of Hong Kong Faculty of Education	2024	6	71	11.83	2	Hong Kong SAR
2	National Research University Higher School of Economics Faculty of Social Sciences	2025	4	10	2.50	2	Russia
3	National Research University Higher School of Economics Institute of Education	2025	4	10	2.50	2	Russia
4	The Chinese University of Hong Kong Department of Curriculum and Instruction	2025	4	12	3.00	1	Hong Kong SAR
5	The Chinese University of Hong Kong Faculty of Education	2025	4	12	3.00	1	Hong Kong SAR
6	Zhejiang University Faculty of Social Sciences	2025	4	16	4.00	1	China
7	Beijing University of Technology College of Economics and Management	2025	3	99	33.00	3	China
8	The Education University of Hong Kong Department of Mathematics and Information Technology	2024	3	21	7.00	2	Hong Kong SAR
9	The Education University of Hong Kong Faculty of Humanities	2024	3	7	2.33	1	Hong Kong SAR
10	The Education University of Hong Kong Faculty of Liberal Arts and Social Sciences	2024	3	21	7.00	2	Hong Kong SAR

3.1.4. Top 10 countries or regions by publication count

As indicated in Table 3, the geographical distribution exhibited a high concentration, wherein China led with 85 articles or 27.78% of the total output, followed by the United States with 43 articles (14.05%) and England with 26 articles (8.50%). The top 10 countries or regions together accounted for 245 country-level publication records, or 80.07% of the 306-article total when summed across countries. As articles co-authored across countries are counted once for each contributing country, this summed share is best interpreted as an indicator of geographic concentration rather than a distinct-article proportion; even so, it suggests that a smaller group of countries currently dominates the research field. Meanwhile, the citation impact varied substantially, wherein Singapore (30.13), Pakistan (22.80), and Malaysia (22.00) attained higher average citations per article than larger producers such as China (16.35), the United States (8.58), and Germany (5.22).

Table 3. Data summary of the top 10 countries/regions by publication count (source: WoS)

Rank	Country/region	PYS	NP	STC	AC/I	h-index
1	China	2023	85	1,390	16.35	15
2	United States	2023	43	369	8.58	8
3	England	2023	26	521	20.04	9
4	Spain	2023	22	254	11.55	7
5	Australia	2023	19	179	9.42	6
6	Saudi Arabia	2024	12	135	11.25	5
7	Malaysia	2024	11	242	22.00	4
8	Pakistan	2024	10	228	22.80	5
9	Germany	2024	9	47	5.22	4
10	Singapore	2023	8	241	30.13	4

3.1.5. Top 10 publication titles (journals) by publication count

As indicated in Table 4, the journal landscape was widely dispersed, wherein the 306 articles were distributed across 157 unique journals, with the top 10 collectively publishing only 84 articles, or 27.45% of the total output. Education Sciences led with 19 articles (6.21%), followed by Education and Information Technologies (14 articles or 4.58%) and Frontiers in Education (11 articles or 3.60%), with the prominence of education-specific journals reflecting that the current field has been approached primarily through the educational lens rather than the computer science or information technology lens, consistent with how education research has itself been mapped bibliometrically [32]. Furthermore, the citation impact diverged from the productivity ranking, wherein the International Journal of Educational Technology in Higher Education attained the highest average of 125 citations per article from only seven publications, followed by the International Journal of Human-Computer Interaction with 42.40 average citations per article from five publications.

Table 4. Data summary of the top 10 PT (journals) by publication count (source: WoS)

Rank	PT	PYS	NP	STC	AC/I	h-index
1	Education Sciences	2023	19	422	22.21	7
2	Education and Information Technologies	2024	14	120	8.57	5
3	Frontiers in Education	2024	11	19	1.73	3
4	Innovations in Education and Teaching International	2024	7	51	7.29	2
5	International Journal of Educational Technology in Higher Education	2023	7	875	125.00	5
6	Behavioral Sciences	2025	6	8	1.33	2
7	Assessment & Evaluation in Higher Education	2025	5	11	2.20	2
8	Cogent Education	2024	5	23	4.60	2
9	Information	2024	5	52	10.40	2
10	International Journal of Human-Computer Interaction	2025	5	212	42.40	3

3.2. Impact analysis

The academic impact of research on GenAI in higher education was appraised through the citation metrics, namely the annual citation trend between 2023 and 2025 and the top 10 most cited articles. A total of 3,646 citations were acquired across the dataset as of the 31 October 2025 extraction date, with the top 10 most cited articles accounting for nearly half of the total citations. Each of the two impact dimensions is examined in turn in the following subsections.

3.2.1. Annual citation trend

The annual citation distribution, as portrayed in Figure 2, exhibited a pronounced upward trajectory from only 36 citations in 2023 to 2,728 citations in 2025, namely a 75-fold increase within just two years that outpaced the 16-fold growth in the number of articles over the same window. The average citations per article also expanded from 3.00 in 2023 to 8.65 in 2024 and to 14.28 in 2025, with 2025 alone accounting for 74.82% of the total citations across the three-year window. Consistent with the omission of one 2026-dated article from the temporal analysis, the cumulative total of 3,646 citations was distributed across 305 articles dated 2023 to 2025, namely an overall average of 11.95 citations per article, which reflected substantial academic engagement with the present field.

3.2.2. Top 10 most cited publications

As illustrated in Table 5, the citation impact was highly concentrated, wherein the 10 most cited articles collectively accounted for 1,816 citations, namely, 49.81% of the total 3,646 citations. The most influential article was Chan and Hu [33], published in the International Journal of Educational Technology in Higher Education, which alone attained 609 citations or 16.70% of the total citations, with its focus on

student perceptions of GenAI defining one of the dominant themes of the current field. The remaining nine of the top 10 most cited articles were distributed across student perceptions and use intentions [34]–[36], academic integrity and student evaluation [37], [38], drivers and consequences of GenAI adoption [39], [40], the application of GenAI to international student success [41], and conceptual mapping of GenAI in higher education [42], with the temporal distribution of four articles in 2023, five in 2024, and one in 2025 reflecting that influential research has continued to emerge as the field has expanded.

Table 5. Data summary of the top 10 most cited articles (source: WoS)

Rank	Title	Source	PT	TC
1	Students' voices on generative AI: perceptions, benefits, and challenges in higher education	[33]	International Journal of Educational Technology in Higher Education	609
2	Challenges and opportunities of generative AI for higher education as explained by ChatGPT	[42]	Education Sciences	269
3	Generative AI tools and assessment: Guidelines of the world's top-ranking universities	[37]	Computers and Education Open	137
4	Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour	[39]	Technology in Society	135
5	Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success	[41]	Applied Sciences-Basel	129
6	Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives	[38]	International Journal of Educational Technology in Higher Education	126
7	Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students	[40]	International Journal of Educational Technology in Higher Education	114
8	Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy	[36]	International Journal of Human-Computer Interaction	107
9	Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt	[34]	British Journal of Educational Technology	106
10	Student perspectives on the use of generative artificial intelligence technologies in higher education	[35]	International Journal for Educational Integrity	84

3.3. Thematic analysis

As shown in Table 6, the multidisciplinary composition of the present field spanned 30 research areas, with education and educational research dominating at 176 articles or 57.52% of the total output, followed by computer science (44 articles) and psychology (25 articles); as an article may be classified under more than one WoS research area, these area counts are non-exclusive and sum to more than the 306-article total. Despite this dominance in publication count, the citation impact diverged at the disciplinary level, wherein engineering attained the highest average citations per article (34.80) from only 10 articles, and social sciences attained 18.82 average citations from 17 articles. Hence, the breadth of disciplinary engagement, including information science and library science (14 articles), business and economics (11 articles), and linguistics (8 articles), reflected that the present field is being approached as an interdisciplinary concern across education, technology, behavioral, and management areas.

Table 6. Data summary of the top 10 research areas by publication count (source: WoS)

Rank	Research area	PYS	NP	STC	AC/I	h-index
1	Education and educational research	2023	176	2,452	13.93	22
2	Computer science	2023	44	504	11.45	9
3	Psychology	2024	25	113	4.52	5
4	Social sciences other topics	2024	17	320	18.82	7
5	Information science library science	2024	14	62	4.43	5
6	Business economics	2023	11	161	14.64	5
7	Engineering	2023	10	348	34.80	4
8	Science technology other topics	2024	10	58	5.80	2
9	Linguistics	2024	8	17	2.13	3
10	Area studies	2025	4	41	10.25	4

4. DISCUSSION

In the current section, the bibliometric results are interpreted in light of established bibliometric theory and prior literature, with the structure of the discussion mirroring the three RQs. Specifically, the

productivity patterns are interpreted against Lotka's law of scientific productivity and Bradford's law of scattering; the citation impact patterns are interpreted against the citation-concentration dynamics of emerging fields; and the thematic composition is interpreted against the multidisciplinary maturation of new research areas. The structure separates the empirical findings from the critical interpretation provided here, making the basis for each interpretation more transparent.

4.1. Discussion of productivity patterns

The productivity findings revealed three patterns that, when interpreted against established bibliometric theory, characterized a field that is rapidly proliferating yet structurally immature. First, the authorship landscape appeared more dispersed than the concentrated authorship core described by Lotka's law of scientific productivity [43], [44]. Specifically, although Lotka's law posits a skewed distribution in which a smaller core of prolific scholars would drive the majority of output, the present results indicated that there was no such core that had emerged after three years of intensive activity, with 979 scholars contributing to 306 articles and no individual author exceeding 0.98% of the total output. Thus, it was suggested not merely that the current field is new, but also that a stable disciplinary core may not yet have formed, which can be interpreted as consistent with the early-stage dynamics of a pre-paradigmatic field [45].

Second, the journal landscape appeared broadly consistent with Bradford's law of scattering [46], although the scattering was unusually wide. Particularly, as documented in Table 4, the journal-level concentration of the 306 articles appeared lower than is typical of more mature specializations, with the top 10 journals accounting for only 27.45% of total output [23], [46]. As such, it was implied that research on GenAI in higher education has yet to have its clear disciplinary home, and is being approached as an applied interdisciplinary concern by editors in education, technology, behavioral sciences, and other related areas, with parallel rather than integrated bodies of knowledge being produced.

Third, the productivity rankings diverged from the citation-impact rankings at every level of analysis, namely, author, institution, country, and journal. For instance, Beijing University of Technology's College of Economics and Management attained 99 citations across only three articles, exceeding the larger-output University of Hong Kong Faculty of Education on a per-article basis, and Singapore (30.13), Pakistan (22.80), and Malaysia (22.00) attained higher average citations per article than China (16.35), the United States (8.58), and Germany (5.22). The divergence indicated that productivity volume was not equivalent to academic impact, with the specific factors underlying this divergence lying beyond what the present bibliometric indicators can determine [27].

4.2. Discussion of citation impact

The citation findings revealed that the academic impact of the current field was both rapidly accumulating and highly concentrated. Specifically, although the number of articles expanded approximately 16-fold from 2023 to 2025, the citation count expanded approximately 75-fold over the same window, indicating that recent publications attained academic traction more rapidly than the publication count alone would suggest. Thus, it was implied that the current field has shifted from initial exploration to research outputs gaining stronger influence within different research communities, with the disproportionate citation-to-publication growth ratio being consistent with the elevated growth rates observed in rapidly proliferating scientific fields [47].

Notably, the impact was unevenly distributed within the dataset, wherein the 10 most cited articles captured 49.81% of the total 3,646 citations, with the single most cited article [33] accounting for 16.70% on its own. While such citation concentration reflects the well-documented skewness of citation distributions, in which a small number of works and authors attract a disproportionate share of citations [27], [48], it was notable that the dominant themes were student perceptions and academic integrity, namely reactive and practice-facing rather than theoretical. As such, the current field has accumulated empirical observations on how students and HEIs are responding to GenAI in a rapid manner, but construct-defining or integrative foundational works appeared not yet to be prominent among the most cited articles, although whether such works have begun to emerge across the wider field cannot be determined from citation counts alone. This pattern, in which a single rapidly cited descriptive article anchors the foundational tier of the field, may differ from fields in which early high-impact works are more often conceptual or methodological in orientation, although a systematic cross-field comparison was beyond the scope of the present study.

4.3. Discussion of thematic composition

The thematic findings revealed that the current field is multidisciplinary in composition yet uneven in disciplinary impact. Specifically, although education and educational research dominated in publication count, the citation impact diverged at the disciplinary level, wherein engineering and social sciences, as detailed in Table 6, attained the highest average citations per article among the top 10 research areas despite producing only modest publication volumes. The asymmetry indicated that disciplinary contributions

integrating technical understanding of GenAI systems with educational theory, or framing GenAI through ethical and social-science lenses, attained disproportionate scholarly attention, even when their publication volumes were modest.

Furthermore, the breadth of disciplinary engagement, spanning 30 research areas, reflected that the current field has not yet consolidated within a single disciplinary home. While the dominance of education and educational research marks a shift from the computer-science- and science, technology, engineering, and mathematics (STEM)-dominated profile of earlier AI-in-higher-education research reported by Zawacki-Richter *et al.* [7], the meaningful contributions from computer science, psychology, business, linguistics, and other domains indicated that the current field is being approached as an applied interdisciplinary concern, similar to other emerging research areas during their formative phase [45]. As such, the current thematic composition is best understood as the early-stage signature of a field still in transition toward consolidation around a unifying conceptual framework.

4.4. Synthesis of the three dimensions

Taken together, three patterns of productivity, citation impact, and thematic composition collectively revealed a coherent characterization of the current field, namely a pre-paradigmatic phase in which empirical activity is outpacing conceptual consolidation. The disproportionate growth in the number of citations relative to the NP reflected rapid absorption of knowledge; however, the absence of prolific authors, the wide journal dispersion, and the descriptive nature of foundational works collectively suggested that the absorption is yet to be channeled through a shared theoretical vocabulary. Thus, the consolidation of the vocabulary is the central theoretical task facing the current field, and the implications of the characterization are elaborated in section 5.

5. IMPLICATIONS AND FUTURE RESEARCH

Drawing on the discussion, this section translates the bibliometric findings into actionable implications across three complementary dimensions, namely practical implications for HEIs, educators, publishers, and policymakers; theoretical implications for the bibliometric study of emerging research fields; and implications for future research directions. In each case, the recommendation is anchored in a specific bibliometric finding from section 3 or interpretation from section 4 rather than general observation. The structure is intended to make the evidentiary basis of every implication transparent and traceable.

5.1. Practical implications

This section offers practical guidance for four stakeholder groups, namely HEIs, educators and practitioners, scholarly publishers and research administrators, and policymakers, in navigating the adoption of GenAI tools in higher education. The stakeholder-specific structure is intended to make the relevance of the present results transparent for different decision-making contexts. For HEIs, the thematic concentration of the most cited articles on student perceptions and academic integrity indicated the practical challenges that HEIs worldwide are actually confronting. Specifically, six of the top 10 most cited articles concentrated on student perceptions or academic-integrity dimensions of GenAI use. Therefore, HEIs should prioritize the development of clearer and context-specific policies on academic integrity and student evaluation [49] rather than waiting for a unified international consensus, which the field has yet to produce [50]. Furthermore, within the subset of records carrying department-level affiliation data, Hong Kong-based HEIs were prominent among the most productive units, accounting for 6 of the top 10 listed institutions in Table 2, suggesting that HEI leaders in other contexts could benefit from monitoring the hubs while adapting relevant practices to local conditions.

For educators and practitioners, the dispersion of articles across many outlets documented in Table 4 made comprehensive monitoring impractical. However, Table 4 indicated that the International Journal of Educational Technology in Higher Education attained the highest average citations per article among the top 10 outlets, namely functioning as a de facto reference journal for foundational work despite a modest publication count. As such, for educators with limited time, monitoring only a small number of journals, particularly Education Sciences, Education and Information Technologies, and the International Journal of Educational Technology in Higher Education, could capture a disproportionate share of influential evidence. The above is further reinforced by the broader trajectory of digital transformation in higher education, in which both student and teacher engagement with digital media has been shown to shape relevant pedagogical practices [51], [52].

For scholarly publishers and research administrators, the unconsolidated journal landscape presented a time-limited opportunity. Specifically, as documented in Table 4, the field has yet to be consolidated around a small core of specialist journals, leaving room for established outlets to build reputations as

destinations for research on GenAI in higher education before the journal core crystallizes. Moreover, research administrators should note the gap between output and impact at the disciplinary level documented in Table 6, where engineering and social sciences each produced relatively few articles but attained the highest average citations per article among the top 10 research areas. Thus, any administrative frameworks that would reward output volume might under-reward the highest-impact work in the present field. Applied bibliometric indicators, supported by information visualization, also serve as useful instruments for HEIs in the decision-making processes [53].

For policymakers, the geographical concentration carried a clear caution. Particularly, the top 3 producing countries reported in Table 3 collectively accounted for 50.33% of total articles, which implied that any policy frameworks derived from the present evidence are implicitly shaped by the educational contexts of a smaller number of countries. Furthermore, the underrepresentation of Latin America, Africa, and other parts of Asia in Table 3 suggested that generalizing the present findings to the contexts is premature. As such, policymakers in underrepresented regions should invest in local research capacity rather than importing policy templates developed in the dominant-producer countries.

In sum, the common ramification across the four stakeholder groups was that evidence-based engagement with GenAI in higher education is feasible now, although it would require acting on patterns that remain volatile, as documented across Tables 1 to 6. Thus, stakeholders who wait for the current field to stabilize before acting might find themselves responding to a landscape that has already moved on. The ramification reinforces the urgency of evidence-based decision-making at the present stage of the field.

5.2. Theoretical implications

Beyond the practical and future-research implications, the present study offered three theoretical contributions to the bibliometric study of emerging research fields. First, the case of post-ChatGPT research on GenAI in higher education provided empirical support for the proposition that classical bibliometric laws, namely, Lotka's law of authorship productivity and Bradford's law of journal scattering, retain interpretive value when applied to emerging fields, but that the magnitude of authorship fragmentation and journal dispersion can be more pronounced during a field's formative phase than in more mature specializations. Specifically, the author-to-publication ratio of 3.2:1 and the wide scattering across 157 journals were both consistent with a highly dispersed, early-stage field, suggesting that the concentration these classical laws describe may emerge only as fields catalyzed by discrete technological events mature.

Second, the present study contributed to the theory of foundational citation accumulation by demonstrating that, in fields catalyzed by rapid technological disruption, foundational citations may accumulate around descriptive and practice-facing observations rather than theoretical contributions, which is a meaningful divergence from the citation-accumulation patterns expected in more conventionally maturing fields, where conceptual or methodological works typically anchor the foundational tier. Specifically, six of the 10 most cited articles in the current dataset concentrated on student perceptions and academic integrity, namely, predominantly reactive, practice-facing themes, with relatively few advancing integrative theoretical models. As such, the present study suggested that field-maturation timelines may need to be reconsidered for technology-catalyzed research areas, where theoretical consolidation may follow rather than precede empirical accumulation.

Third, the present study contributed a transferable three-dimensional analytical framework, integrating productivity, citation impact, and thematic composition, which underpins a dedicated three-dimensional bibliometric performance map of post-ChatGPT GenAI research in higher education and which other bibliometric researchers can adopt or adapt for the study of comparable rapidly emerging fields. The framework is consistent with established bibliometric guidelines [8], [23] but is distinguished by its tripartite analytical structure, in which each dimension is examined both descriptively and through interpretive comparison with established bibliometric laws and prior literature. As such, the framework offers a transferable template for future bibliometric studies of post-ChatGPT GenAI research in adjacent areas, including K–12 education, professional education, and informal learning, where similar developmental dynamics may be expected.

5.3. Implications for future research

The bibliometric findings reported in section 3 and the interpretations elaborated in section 4 collectively pointed to four directions for future research. The four directions correspond directly to the four structural patterns identified in the present results, namely geographical concentration, thematic concentration, methodological homogeneity, and theoretical fragmentation. Each direction is paired with the specific finding that motivates it.

The first direction was geographical diversification, motivated by the citation-impact rankings, where smaller producers such as Singapore, Pakistan, and Malaysia attained higher average citations per article than larger producers such as China, the United States, and Germany. The per-article advantage of

smaller-output countries implied that the research capacity of underrepresented regions is undervalued by the current output-centric assessments. Thus, future research in Latin America, Africa, and other parts of Asia is not only a matter of equity but also a matter of empirical necessity; several smaller-output countries already attain higher per-article citation impact than the largest producers, suggesting that such under-represented contexts may yield findings that leading-country evidence alone does not fully capture [50].

The second direction was thematic expansion, motivated by the thematic concentration of the most cited articles. Particularly, 6 of the top 10 most cited articles concentrated on student perceptions or academic integrity, with limited representation of faculty development [54], measurable learning outcomes, curriculum redesign, longitudinal institutional change, and equity dimensions. As such, priority thematic gaps for future research include the five underrepresented areas [55]. Moreover, the divergence between publication count and citation impact at the disciplinary level reported in Table 6, in which engineering and social sciences attained the highest average citations per article despite producing relatively few articles, suggested that works integrating technical understanding of GenAI systems, including natural-language processing and LLMs, with educational concerns will be disproportionately rewarded [56].

The third direction was methodological strengthening, motivated by the temporal concentration of citations and the foundational nature of the most cited articles. Specifically, citations were heavily concentrated in 2025, while the most cited articles, as listed in Table 5, were predominantly cross-sectional descriptive and survey-based studies. The design profile was appropriate for an early-stage field but insufficient for establishing causal or developmental claims. Thus, future research should incorporate longitudinal, experimental, and mixed-methods designs to capture how GenAI adoption and its educational effects would evolve over time [57]. Furthermore, at the bibliometric level, subsequent reviews should extend beyond the WoS Core Collection to include Scopus, ERIC, and regional indices, which would help mitigate the database-coverage and language biases, with advanced network-analytic techniques applied, namely, co-citation analysis, bibliographic coupling, and keyword co-occurrence mapping [23], [58].

The fourth direction was conceptual consolidation, motivated by the discussion of the descriptive nature of foundational works. Specifically, although citation concentration is characteristic of emerging fields, the dominant themes in the current foundational works were reactive and practice-facing rather than theoretical. As such, integrative conceptual papers, systematic reviews, and meta-analyses, which would synthesize the rapidly accumulating empirical findings into coherent models, will be particularly useful [7], [11]. Through the synthesis, the current collection of parallel observations can be transformed into a cumulative research program.

Collectively, the common ramification across the four directions was that the most useful future research will be both broader and deeper than most current work, namely broader in its geographical, thematic, and methodological scope, and deeper in its commitment to building theory rather than only documenting practice. Each of the directions is anchored in a specific finding from section 3 or interpretation from section 4, making the present research agenda traceable rather than aspirational. Pursued together, the directions will help transform the current rapidly proliferating empirical activity into a cumulative and theoretically integrated research program.

6. LIMITATIONS

There are several limitations in the present bibliometric analysis. First, the use of only the WoS Core Collection might have omitted relevant articles indexed in other academic databases such as ERIC, Scopus, and Google Scholar, all of which exhibit substantial coverage variation relative to WoS [58]. Furthermore, as the analysis was performed among only English-published articles, certain linguistic bias might be introduced when valuable contributions from non-Anglophone regions, where research on GenAI in higher education is also actively advancing, might be neglected. As bibliometric analysis emphasizes quantitative indicators over qualitative ones in terms of research quality or methodological rigor, citation counts only indicate academic attention instead of scientific validity [8]. The present results only offer a short-term view due to the rapidly developing field of research on GenAI in higher education, in which the landscape may profoundly alter as the field continues to become more mature after 2025. In addition, the institutional analysis draws on the 132 of 306 records (43.1%) that report department-level affiliation data, and the unreported share may not be evenly distributed across regions. The annual publication and citation counts assign each article to the earliest year for which a WoS date is available, including early-access dates, so they may differ from counts based on the final issue year. As Hong Kong addresses are recorded by WoS under China, Hong Kong is not represented as a separate country or region in Table 3. Finally, the TI search strategy may not capture articles that address generative AI in higher education in the abstract or keywords but not in the title, which may introduce a recall limitation.

7. CONCLUSION

In the present study, a PRISMA-guided bibliometric performance analysis was conducted on 306 articles on GenAI in higher education, indexed in the WoS Core Collection between 2023 and 2025, with the aim of mapping the research productivity, citation impact, and thematic composition of the current rapidly emerging field. The analysis was structured around three RQs and addressed each in turn through productivity indicators, impact indicators, and thematic indicators, with the interpretation of the patterns and translated into actionable implications. The structure provided a transparent path from empirical findings to applied recommendations and theoretical contributions.

Three main contributions emerged from the present study. First, the present study contributed a dedicated three-dimensional bibliometric performance map of post-ChatGPT research on GenAI in higher education, integrating productivity, citation impact, and thematic composition, and characterizing the field as one of rapid publication growth, fragmented authorship, concentrated citation impact, and broad interdisciplinary engagement across 30 research areas. Second, the present study advanced the bibliometric study of emerging research fields by demonstrating that classical bibliometric laws retain interpretive value for technology-catalyzed fields, although the magnitude of authorship fragmentation and journal dispersion can exceed conventional expectations during the formative phase. Third, the study offered a transferable three-dimensional analytical framework, integrating productivity, impact, and thematic composition, which other bibliometric researchers can adopt for the study of comparable rapidly emerging fields. Several limitations qualify these contributions; accordingly, the present results are best interpreted as a snapshot of the WoS-indexed, English-language segment of the field between 2023 and 2025.

Four directions for future research follow from the present findings. First, geographical diversification is required, particularly through research in Latin America, Africa, and underrepresented parts of Asia, where per-article citation performance suggested considerable unrealized capacity. Second, thematic expansion should move beyond student perceptions and academic integrity to address faculty development, measurable learning outcomes, curriculum and assessment redesign, and longitudinal institutional change. Third, methodological strengthening should incorporate longitudinal, experimental, and mixed-methods designs and extend bibliometric reviews to multi-database and multi-language coverage with advanced network-analytic techniques. Fourth, conceptual consolidation through integrative syntheses and theory-building reviews is needed to transform the current collection of parallel empirical observations into a cumulative research program. Sustained and coordinated effort along the four directions will be essential, so that research on GenAI in higher education will support, rather than merely describe, the transformation of teaching, learning, and assessment at scale.

ACKNOWLEDGMENTS

The authors thank the Science, Technology, Engineering, and Mathematics (STEM) Research Group at the Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, for its support.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
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P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [TGT], upon reasonable request.

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