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Generative AI in academic research : A comprehensive bibliometric analysis using OpenAlex database

Ajay Kumar Chaubey

This research examines the progression of Generative AI in scholarly work through a bibliometric analysis of 1,329 articles from the past two decades, indexed in the OpenAlex database. The results demonstrate a swift annual growth rate of 36.01%. The fields of Computer Science and Artificial Intelligence emerged as the primary research areas, establishing the intellectual backbone of the discipline. The United States was recognized as the foremost contributor to research, with Mike Perkins noted as the most active author. Analyses of keyword co-occurrence and thematic trends illustrate a strong multidisciplinary landscape, with notable growth into areas such as Psychology, Political Science, Engineering, Business, and Medicine. The findings also suggest a transition from discussions centered on specific tools to more expansive, application-focused, and interdisciplinary research. In summary, the research highlights the crucial role of Computer Science and Artificial Intelligence, while also underscoring the growing incorporation of Generative AI across various academic fields, offering valuable insights for future research strategies and policy development.

Keywords: *Generative AI, Artificial Intelligence, Scientometrics, Bibliometric, Open Alex, Academic research.*

Ajay Kumar Chaubey
Prime Minister College of Excellence
Govt. Rajnarayan Smriti College
Waidhan District Singrauli
Madhya Pradesh
India

ORCID-ID
0000-0003-4925-7723

E-mail
ajaybhu21@gmail.com

1. Introduction

John McCarthy originally used the term artificial intelligence (AI) in the 1950s, and it refers to "the science and engineering of making intelligent machines" [1]. Recent developments in artificial intelligence and its uses have raised ethical, legal, and technological issues for our society on many levels and in a range of contexts. Artificial general intelligence systems that can replicate human

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behaviour, emotions, and intelligence are the result of research into artificial intelligence [2]. Generative AI(GenAI) refers to a broad category of "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, and audio from training data" [3]. GenAI tools are sophisticated (and mostly undocumented) systems that expand upon Large Language Models (LLMs) for the creation of textual content [4]. It can transform research practices by enabling new possibilities for exploration, analysis, and innovation [5]. [6] Emphasise that Generative Pre-trained Transformers (GPTs) are especially disruptive in education, with their greatest impact expected in enhancing knowledge-based productivity. GenAI gained popularity after ChatGPT, the first model with an easy-to-use chat interface that allowed users to engage with the underlying model in discussions that resembled those of a human, was released in November 2022. This interactive technology resembles human thought processes and speech, which has greatly increased its appeal of GenAI [7], including in higher education [8], academic writing [9] and scientific research [10]. Recently, GenAI has been presented as an innovative solution for various tasks in scientometrics, such as identifying new research subjects [11]. Other new uses include identifying disruptive research [12], classifying research publications according to metadata [13], and assessing the quality of research [14].

However, without adequate oversight, AI can also be quite dangerous and produce conclusions that are skewed, faulty, or even unscientific [15, 16]. Therefore, as other studies indicate, it is essential that the academic community maintains its vigilance while creating frameworks, procedures, and instruments to direct and control AI's use in research [17].

Although scholarly interest in Generative AI in academic research has expanded rapidly, especially after the release of ChatGPT in 2022 existing research has largely emphasised technical, ethical, and application-specific perspectives, such as education, healthcare and industry use cases. To the best of our knowledge, there is a lack of research that systematically examines the intellectual structure, thematic evolution, and interdisciplinary dynamics of Generative AI scholarship itself using large-scale, open-access bibliometric data. Consequently, this study adopts bibliometric analysis to present the state of the intellectual structure and emerging trends in Generative AI research, addressing a gap not covered by prior studies. To address this research gap, the present study employs bibliometric analytical techniques to examine the intellectual structure of Generative AI in academic research over the last two decades. Accordingly, the study addresses the following research questions:

- What are the publication growth patterns and cumulative trends in Generative AI research over time?
- Who are the most influential contributors, and what constitutes the intellectual and conceptual foundations of the field (key authors, core references, and dominant keywords)?
- Which authors and countries lead global research output, and does author productivity conform to established bibliometric distributions such as Lotka's Law?

- What major thematic clusters structure Generative AI research, and how have these themes evolved in terms of emerging and declining areas?
- What do keyword co-occurrence and bibliographic coupling networks reveal about the field's intellectual cohesion, collaboration patterns, and sub-disciplinary structure?

In summary, the research emphasises the essential role of Computer Science and Artificial Intelligence, while also underscoring the increasing incorporation of Generative AI within various academic fields, providing valuable perspectives for future research strategies and policy formulation. The rest of the paper is structured in the following manner. The following section examines pertinent literature while delineating the study's goals and methodology. The next part showcases the bibliometric results, which include productivity metrics of authors and countries, as well as intellectual and conceptual frameworks, thematic development, collaboration trends, and network analyses. The discussion interprets the principal findings and places them in the context of the wider Generative AI research field. Lastly, the conclusion encapsulates key insights and suggests avenues for future research.

2. Review of Literature

The existing literature highlights the significant influence of Generative AI (GenAI) on academic research, especially in areas such as literature synthesis, data analysis, and scholarly writing. Research consistently shows that GenAI improves the efficiency of research by speeding up the integration of knowledge, aiding in the interpretation of complex data, and helping with the preparation of manuscripts. Its use is particularly notable in higher education and healthcare, where the automation and enhancement of analytical processes are transforming research workflows Ning et al. [18]; Lin [20]. Despite the efficiencies gained, many ethical, governance, and integrity issues have surfaced. Researchers point to problems surrounding author attribution, transparency, accountability, and the reliability of data, suggesting that the incorporation of GenAI necessitates well-established regulatory standards (Zohny, McMillan, and King. [21]; Schlagwein and Willcocks [22]; Spector-Bagdady [19]). Worries regarding biased training data and the lack of clarity in algorithms increase the likelihood of skewed interpretations, biased outcomes, and the perpetuation of systemic inequalities in the production of knowledge. These concerns highlight the importance of responsible oversight and institutional protections Kurtz et al. [24].

At the policy level, the lack of comprehensive and enforceable regulatory frameworks continues to be a significant issue. Scholars warn that the swift spread of GenAI technologies might exceed academia's ability to address their ethical and methodological concerns (Kunda [25]; Rios-Campos et al. [26]; Al-Zahrani [23]). As a result, governance initiatives are developing at various levels, including among scholarly publishers, publication guidelines, higher education institutions (HEIs), and national or international legislative bodies (Li, Cai and Cheng [27]).

In higher education, institutional policies are increasingly focused on integrating AI into teaching and research, concentrating on aspects such as academic integrity, requirements for disclosure, and preventing misconduct that is aided by AI (Moore and Lookadoo [28]; Song [29]; Guillen-Yparrea and Hernandez-Rodriguez [30]). Concurrent discussions highlight the significance of initiatives aimed at AI literacy to ensure that researchers and students possess the critical evaluation skills needed for responsible use (Chen, Tallant, and Seliget [31]). Wider ethical considerations call for adaptable and reflective frameworks for research ethics to steer AI-driven scholarship, Chaaban [32]; Alduais et al. [33].

Overall, the research points to two main conclusions: GenAI greatly improves research output and knowledge creation, but its unregulated use brings risks to authorship standards, transparency, bias reduction, and the integrity of academia. Although conversations around governance and policy are increasing, the current scholarship is mainly normative and disjointed, underscoring the importance of comprehensive and organized examinations of the changing research environment.

3. Objectives of the study

The main aim of this investigation is to visualise the status of Generative AI in Academic Research based on publications output as retrieved from the open Alex database.

1. To explore the growth of Generative AI in Academic Research literature.
2. To identify three plots (author, cited reference & keyword)
3. To identify the author productivity and country's scientific productivity
4. to reveal the research trends and research theme
5. To analyse the co-occurrence and bibliographic coupling pattern in Generative AI in Academic Research literature.

4. Methodology

The bibliographic data for this research were obtained from OpenAlex, the largest open-access bibliographic database globally, chosen for its extensive, organised, and clear scholarly metadata, along with API support that facilitates reproducible large-scale analyses. To obtain the most precise results, we use the following search string: ("Generative AI" OR "Large Language Models" OR "ChatGPT") AND ("Academic Research" OR "Higher Education" OR "Scholarly Publishing").

The research encompassed publications from 2005 to 2025, allowing for a comprehensive analysis of the field's evolution. To uphold academic integrity, the dataset focused exclusively on original research articles, conference proceedings, books, book chapters, preprints, and review articles. The search was carried out during the first week of August 2025. Retrieved records were manually reviewed to eliminate duplicates, and the resulting dataset was exported in CSV format for further analysis.

Table 1
Annual Growth of Publications

Year	Number of Articles
2005-2009	1
2010-2014	1
2015-2019	5
2020	2
2021	8
2022	6
2023	272
2024	565
2025	469
Total	1329

A bibliometric analysis and visualisation were carried out employing Bibliometrix (through Biblioshiny) and VOSviewer. Bibliometrix enabled the statistical analysis and mapping of scientific literature [34], while VOSviewer was utilised to create and visualise bibliographic networks [35]. Further analyses were performed in RStudio to uncover research patterns and identify emerging trends.

5. Results

5.1 *Annual growth rate*

Table 1 illustrates the annual growth of publications on Generative AI in Academic Research from 2005 to 2025, with an average annual growth rate of 36.01%. From 2005 to 2021, the volume of scholarly output was consistently low and stable, suggesting minimal research engagement in this area. A dramatic and exponential rise was noted starting in 2022. The number of publications saw a significant increase in 2023, followed by 2024. The reduced total for 2025 is based on incomplete data gathered up to 8 August 2025. The increase following 2022 aligns with the launch of ChatGPT, which greatly boosted academic curiosity in generative AI [36]. The notable expansion from 2023 to 2024 indicates a heightened focus on the use of generative AI, ethical considerations, its integration into teaching, and its wider effects on society [37].

5.2 *Three-Field Plot analysis*

Three-field plot analysis is used in bibliometric research to assess academic entities such as authors, journals, and institutions in a methodical manner [34]. We conducted an analysis on the link between keywords, cited reference, and authors s using a three-field plot created with Biblioshiny in RStudio (Figure 3). The three-field plot illustrates the

connections between authors (AU), cited references (CR), and author-provided keywords (KW_Merged) in an OpenAlex bibliographic dataset. It maps how authors reference particular works and how those works correspond to the keywords in their publications, revealing clusters of scholars who rely on similar literature and focus on related research themes. The plot features three groups of nodes, each representing a different field: authors in the center, cited references on the left, and keywords on the right. Gray lines connect these nodes, with line thickness indicating the strength or frequency of the relationship—a thicker line shows that an author or group of authors often cites a specific reference or frequently uses a given keyword.

Author–Keyword Relationship:

Zhicheng Lin shows a strong association with Computer Science, while Mike Perkins is also linked to the field, though less prominently. Cecilia Ka Yuk Chan is connected to Artificial Intelligence, and Jasper Roe to Psychology. The visualization further indicates author–topic linkages across diverse areas, including Generative Grammar, Engineering, Political Science, Law, Mathematics Education, Sociology, Engineering Ethics, Data Science, Medicine, Philosophy, Mathematics, Pedagogy, Knowledge Management, Business, and Linguistics.

Author–Cited Reference Relationships:

The cited references appear on the left, showing their connections to various authors. Zhicheng Lin, Mike Perkins, and Cecilia Ka Yuk Chan cite a common set of reference

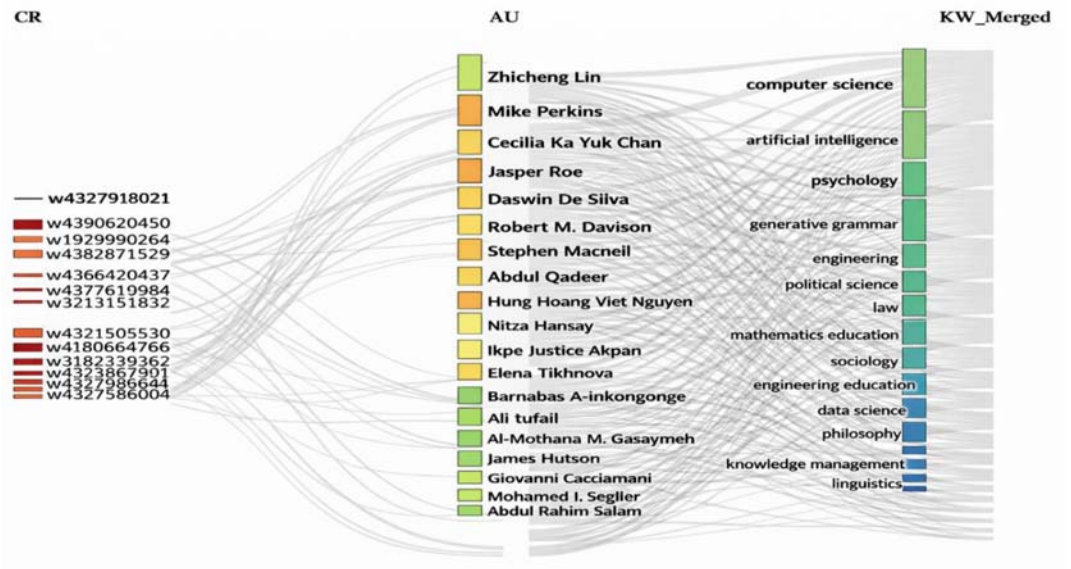

Figure 1

Three Field Plot displays the keyword, author and the source

documents—w4327918021, w4360620450, w1979290264, w4348257512, w4366420437, w4317910584, w4321351832, and w4321605350—indicating they are part of a research community who share ideas and citations. A similar pattern is seen among Hung Hoang Viet Nguyen, Nate Breznau, and Lilia Raitskaya, who also share a common set of cited references (Figure 1).

Keyword Diversity and Specialization:

The keywords reflect the dataset's diverse range, encompassing areas from computer science and artificial intelligence to practical domains like knowledge management and education. Connections between authors and keywords showcase specific research interests within this wider context. Connections between authors and keywords highlight specific research areas within the larger context. Analyzing the references related to Zhicheng Lin and Mike Perkins aids in pinpointing key studies in the discipline. The visual representation also displays several authors linked to various fields, demonstrating their involvement in interdisciplinary work. For example, associations with both "computer science" and "knowledge management" indicate a role in bridging technical and applied management sectors.

5.3 *Most Prolific Authors*

Table 2 presents the top ten authors ranked by their fractionalized article contributions. Mike Perkins dominated the list. Mike Perkins leads with 9 publications, corresponding to 3.28 fractionalized articles, followed by Jasper Roe with 8 publications and 3.12 fractionalized articles. Cecilia Ka Yuk Chan stands out with the highest fractionalized contribution (3.50) despite having only 4 publications, indicating a higher degree of sole or lead authorship. Authors such as Hung Hoang Viet Nguyen and Nate Breznau each have 5 publications,

Table 2

Most Productive Authors in Generative AI in Academic Research during 2005-25

Authors	Articles	Articles Fractionalized
MIKE PERKINS	9	3.28
JASPER ROE	8	3.12
HUNG HOANG VIET NGUYEN	5	2.50
NATE BREZNAU	5	2.50
STEPHEN MACNEIL	5	0.89
CECILIA KA YUK CHAN	4	3.50
DASWIN DE SILVA	4	0.63
ELENA TIKHONOVA	4	2.00
GIOVANNI CACCIAMANI	4	1.44
IKPE JUSTICE AKPAN	4	1.23

both yielding 2.50 fractionalized articles, reflecting shared authorship. In contrast, Stephen Macneil and Daswin De Silva display relatively low fractionalized contributions (0.89 and 0.63 respectively), suggesting a stronger focus on collaborative works. The variation in fractionalized scores highlights differences in authors' individual contributions and authorship patterns within the dataset.

$$\text{Articles Fractionalized for Author A} = \sum_{i=1}^{n} \frac{1}{N_i}$$

Where:

- n = total number of articles authored by A
- N_i = total number of authors on article i
- $\frac{1}{N_i}$ = fractional share of credit for that article

Table 3

Author Productivity through Lotka's Law

Documents written	No. of Authors	Proportion of Authors	Theoretical
1	3418	0.912	0.67
2	267	0.071	0.167
3	45	0.012	0.074
4	10	0.003	0.042
5	3	0.001	0.027
8	1	0	0.01
9	1	0	0.008
26	1	0	0.001

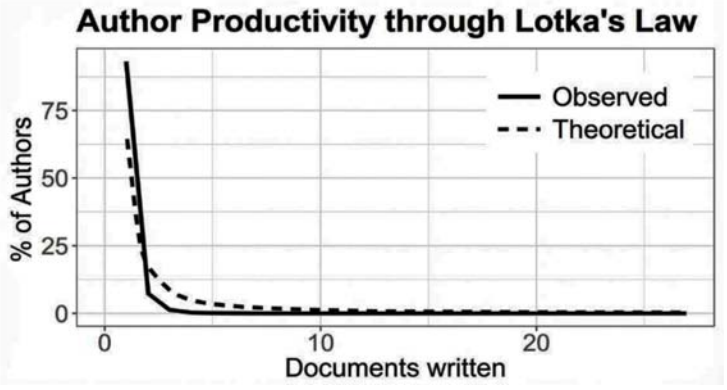

Figure 2

Author Productivity throw Lotka's Law

The figure 2 illustrates the distribution of author productivity in accordance with Lotka's Law. The dotted line showcases the theoretical distribution, whereas the solid line displays the actual (observed) data. According to Lotka's Law, the quantity of authors who publish n articles is roughly proportional to $1/n^2$ of those who publish only one article. This inverse-square correlation is clear in the sharp decrease from one publication to two and further. The distribution shows a significant number of authors with low productivity, which is reflected in the pronounced peak at one published document on the y-axis (percentage of authors). In contrast, the tally of authors drops steeply as the number of publications rises, creating a lengthy tail extending to the right on the x-axis. This trend implies that a limited number of researchers are responsible for a substantial number of publications, while the vast majority only produce one or a few of papers.

This kind of distribution illustrates the cumulative advantage dynamics, often referred to as the Matthew Effect, where a small group of highly productive authors leads in scholarly contributions. The strong correlation between the actual (solid) curve and the expected (dotted) curve suggests that the dataset generally aligns with Lotka's Law, validating a standard bibliometric productivity trend in Generative AI research.

5.4 *Author Local Impact*

Author local impact measure as a bibliometric metric to gauge an author's influence within a designated dataset or research area instead of across all disciplines. Table 4 displays essential metrics—h-index, g-index, m-index, total citations (TC), and number of publications (NP)—that are utilized to evaluate this localized influence. The PY_start column denotes the year when each author's publishing journey commenced, offering context regarding the duration of their career.

Table 4

Author Local Impact: Top Ten authors

Author	h_index	g_index	m_index	TC	NP	PY_start
JASPER ROE	4	8	1.333	76	8	2023
MIKE PERKINS	4	8	1.333	76	9	2023
ROBERT M. DAVISON	4	4	1.333	72	4	2023
ZHICHENG LIN	4	4	1.333	124	4	2023
CECILIA KA YUK CHAN	3	4	1	733	4	2023
DASWIN DE SILVA	3	4	1	48	4	2023
ABAYOMI AROWOSEGBE	2	2	1	12	2	2024
ABDUL RAHIM SALAM	2	3	1	12	3	2024
ADELA BÂRÃ	2	2	2	12	2	2025
AL-MOTHANA M. GASAYMEH	2	3	1	14	3	2024

Top tier (High Impact): Jasper Roe and Mike Perkins demonstrate strong local impact, each with TC = 76, h-index = 4, g-index = 8, and m-index = 1.333, indicating both productivity and rapid citation growth since 2023. Zhicheng Lin records the highest TC (124) with an h-index of 4, reflecting highly influential work. Robert M. Davison also has an h-index of 4 and m-index of 1.333, though with lower TC (72) and g-index (4), suggesting consistent citation performance rather than a single highly cited publication.

Mid-Tier (Emerging Impact): Cecilia Ka Yuk Chan and Daswin De Silva each have an h-index of 3 and g-index of 4. Cecilia's high TC (733) suggests impact concentrated in one or a few highly cited works, whereas Daswin's TC (48) reflects more evenly distributed citations. Their m-index of 1 indicates steady early-career growth.

Lower tier (Early carrier): Abayomi Arowosegbe, Abdul Rahim Salam, Adela Barã, and Al-Mothana M. Gasaymeh have h-indices of 2 with lower TC values. Given their recent publication start years (2024–2025), these metrics are expected and likely to increase with further publications and citations.

In table 5 the plot shows the countries' research output according to the associated authors' affiliations. It distinguishes between articles that come from international cooperation (MCP) and those that come from a single nation (SCP). The MCP Ratio represents the fraction of a country's publications that include international collaboration.

This analysis examines research output on a national scale and the trends in international collaboration. The United States is at the forefront with the highest number of publications (106), yet it has a low MCP ratio (12.3%), suggesting a robust domestic research capacity (SCP = 93) with minimal dependence on international partnerships. The United Kingdom (33), Australia (29), and India (27) display a well-balanced distribution of domestic and

Table 5

Corresponding author country and their contribution

Country	Articles	Articles %	SCP	MCP	MCP %
USA	106	8	93	13	12.3
UNITED KINGDOM	33	2.5	21	12	36.4
AUSTRALIA	29	2.2	22	7	24.1
INDIA	27	2	19	8	29.6
CHINA	24	1.8	13	11	45.8
CANADA	16	1.2	13	3	18.8
HONG KONG	13	1	8	5	38.5
SAUDI ARABIA	8	0.6	7	1	12.5
GERMANY	7	0.5	3	4	57.1
KOREA	7	0.5	5	2	28.6
Other Countries	140	10.53	105	35	25.00

collaborative research, indicating stable research infrastructures. China, despite a lower publication count (24), demonstrates high international engagement (MCP = 45.8%). European countries such as Italy (60%) and Germany (57.1%) exhibit even stronger collaborative patterns, highlighting integrated regional research networks. Sweden and the Netherlands (both 40%) also maintain substantial international partnerships. In contrast, Turkey and South Africa show no multi-country publications, indicating a domestic focus. Saudi Arabia (12.5%) and the UAE (16.7%) have limited collaboration, whereas Hong Kong (38.5%), Malaysia (50%), and Vietnam (50%) display strong international dependence to enhance research capacity. **The Other Countries category, featuring an MCP of 25%, suggests a moderate degree of international cooperation among smaller or emerging research nations, highlighting the growth of global research networks**.

The results indicate various national approaches: countries focused on research depend on strong internal frameworks, European nations prioritize collaborative networks, and developing countries utilize global partnerships to enhance academic output.

5.5 *Countries' Scientific Production*

The top nations are listed by their frequency of scientific production ("Freq") in the table, which quantifies the data displayed on figure 3. The table 6 in the "Freq" column show how many scientific papers or documents each nation produced over a given period of time or dataset.

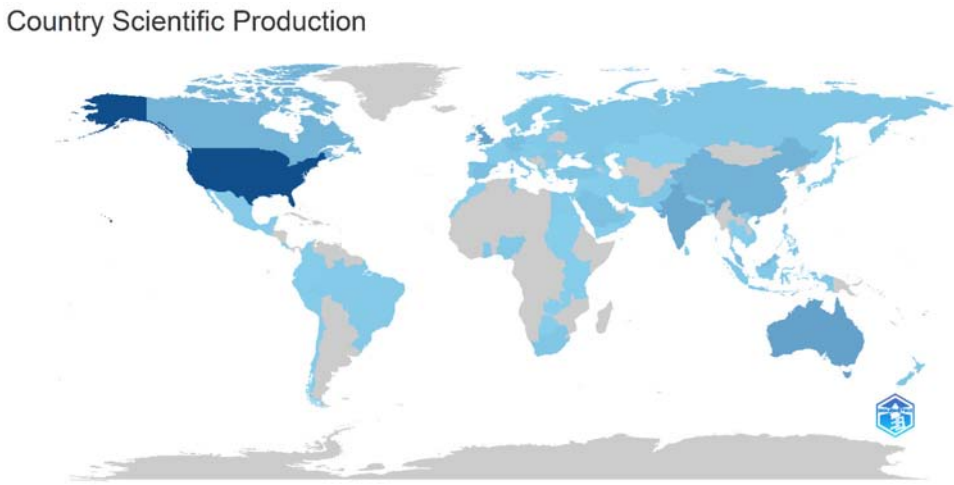

Figure 3

Country Scientific production

The figure 3 illustrates research output is represented through different shades of blue, where deeper hues signify increased productivity. The United States tops the field of

Table 6

Country Scientific production

Country	Freq.
USA	235
AUSTRALIA	77
UK	74
INDIA	65
CANADA	46
MALAYSIA	31
CHINA	26.5
GERMANY	25
SPAIN	25
SAUDI ARABIA	22

Generative AI in Academic Research with a score of 235, indicated by its deepest shade. The United Kingdom (74) and Australia (77) also make significant contributions, while Canada (46) and India (65) show considerable output as well. Malaysia, China, Germany, and Spain all have frequencies exceeding 25, suggesting a moderate level of productivity, while Saudi Arabia (22) is demonstrating growing involvement. In general, Figure 3 and Table 6 illustrate that the distribution of scientific output around the world is unequal, with research primarily focused in a small number of leading countries, especially the United States.

5.6 *Highly Cited Country*

Table 7 shows that ranks nations according to their Average Article Citations and Total Citations (TC). The table shows which nations have the highest rates of research citations as well as the average effect of their articles.

The TC column indicates the total number of citations by country. The United States is at the forefront with 1,235 citations, signifying both substantial productivity and widespread research impact in Generative AI within Academic Research. The United Kingdom is right behind with 1,207 citations, while Canada (883), Hong Kong (759), Australia (568), and Poland (542) also show significant contributions. Average citations per article provide a clearer measure of research quality. France records the highest average (234.50), indicating highly impactful publications despite lower output. Poland (135.50) shows a similar pattern of concentrated high impact. Hong Kong (58.38) and Canada (55.19) also maintain strong per-article influence. In contrast, the United States (11.76) and India (10.74), despite high total citations, have lower average impact per publication, reflecting large output volumes rather than high citation intensity per paper.

Table 7
Highly Cited country

Country	No of publication	TC	Average article citations
UNITED STATES	105	1235	11.76
UNITED KINGDOM	33	1207	36.58
CANADA	16	883	55.19
HONG KONG	13	759	58.38
AUSTRALIA	29	568	19.59
POLAND	04	542	135.50
FRANCE	02	469	234.50
CHINA	21	447	21.29
GERMANY	7	291	41.57
INDIA	27	290	10.74

Overall, while the United States and the United Kingdom lead in total citation numbers, nations like France and Poland show higher average impact per article, emphasizing the difference between the quantity of research and its quality.

5.7 *Highly Cited Papers*

Table 8 list the top ten globally cited documents in Generative AI in academic research ranked by total number of citations. Jürgen Rudolphet et al. (2023) with 1,273 total citations and an annual citation rate of 424.33, this seminal research work is regarded as leader, occupying the top position in both lists. Cecilia Ka Yuk Chan (2023) with 655 total citations and an annual citation rate of 218.33, this work comes in second on both lists. Günther Eysenbach (2023) with 622 total citations and an annual citation rate of 207.33, this work likewise ranks in the top three for both measures.

The fact that these three papers are at the top of both lists demonstrates how immediately and significantly they have affected the scientific community. Since their recent release in 2023, they have not only amassed a sizable total number of citations, but they have done it at an extremely rapid pace. In broader perspective, we can observe that with 508 total citations, David L. Cooperrider's (2013) work is the only one to rank in the top five in terms of overall citations but not citations per year. This demonstrates its enduring, long-term impact. Ismail Dergaa (2023) and Pawan Budhwar (2023) are the papers that rank in the top five for Citations Per Year but not for Total Citations. This demonstrates their growing significance and extremely high first citation rate.

This finding reveals that recent, high-quality research is being quickly recognized and cited, with a few papers showing both a massive overall impact and a rapid pace of citation accumulation.

Table 8

Top ten globally cited documents in Generative AI in Academic Research

Paper	DOI	TC	TC per Year	Normalized TC
JÜRGEN RUDOLPH, 2023, Journal of Applied Learning & Teaching	10.37074/jalt.2023.6.1.9	1273	424.33	31.73
CECILIA KA YUK CHAN, 2023, International Journal of Educational Technology in Higher Education	10.1186/s41239-023-00408-3	655	218.33	16.32
GÜNTHER EYSENBACH, 2023, JMIR Med Education	10.2196/46885	622	207.33	15.50
DAVID L. COOPERRIDER, 2013, Advances in Appreciative Inquiry	10.1108/s1475-9152(2013)0000004001	508	39.08	1.00
ISMAIL DERGAA, 2023, Biol Sport	10.5114/biolsport.2023.125623	507	169.00	12.64
PAWAN BUDHWAR, 2023, Human Resource Management Journal	10.1111/1748-8583.12524	468	156.00	11.66
ROSARIO MICHEL-VILLARREAL, 2023, Education Science	10.3390/educsci13090856	421	140.33	10.49
JOSEPH CRAWFORD, 2023, Journal of University Teaching and Learning Practice	10.53761/1.20.3.02	390	130.00	9.72
TAREQ RASUL, 2023, Journal of Applied Learning & Teaching	10.37074/jalt.2023.6.1.29	333	111.00	8.30
KRZYSZTOF WACH, 2023, Entrepreneurial Business and Economics Review	10.15678/eber.2023.110201	312	104.00	7.78

5.8 *Research Trends Analysis*

We analyzing the most commonly used research keywords in Figure 4, The network shows links between different areas of study, presenting a multidisciplinary landscape. Each node's (keyword's) size indicates how frequently it appears in the dataset. Co-occurrence is indicated by the lines (edges) that connect the nodes; thicker lines imply a stronger correlation between the terms that are connected. Distinct communities (topics) inside the network have been found by the clustering method (Walktrap), and they are represented by various colors.

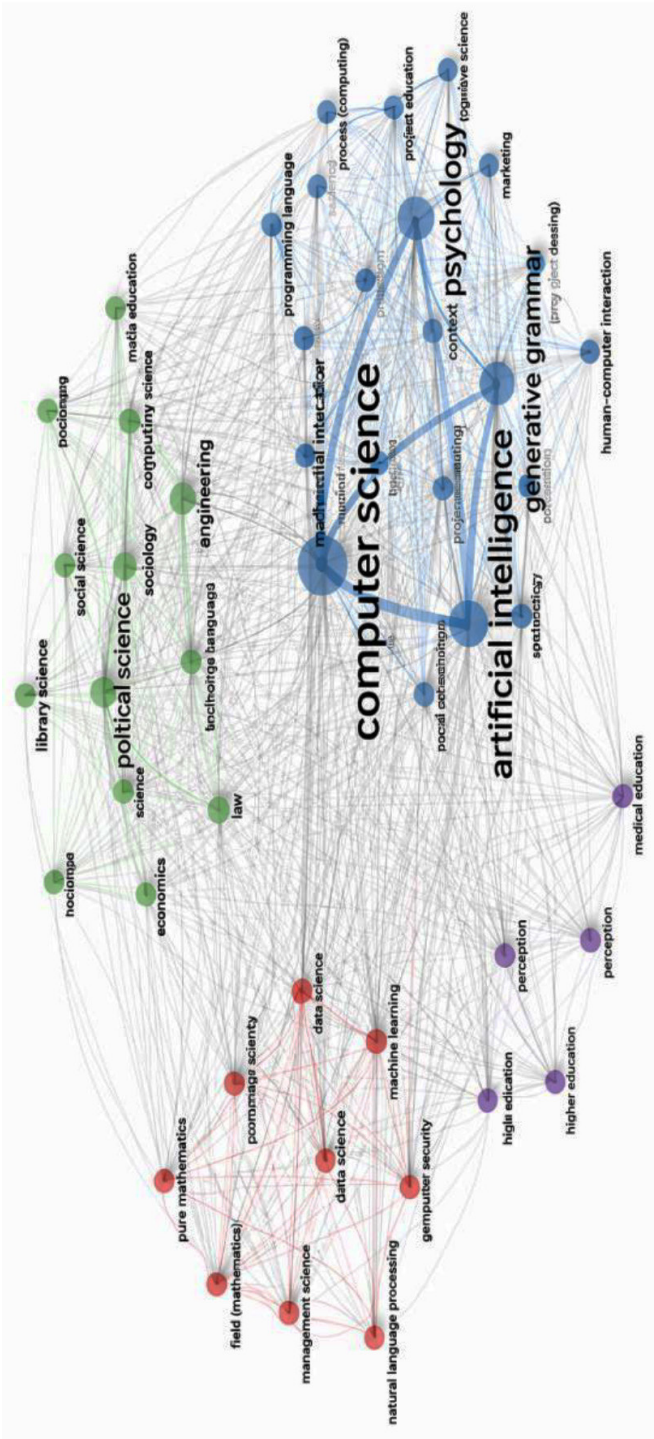

Figure 4
Co-occurrence network of keywords

The most frequent keywords were related to Computer Science, Artificial Intelligence, Psychology, Generative Grammer, Engineering and Political Science.

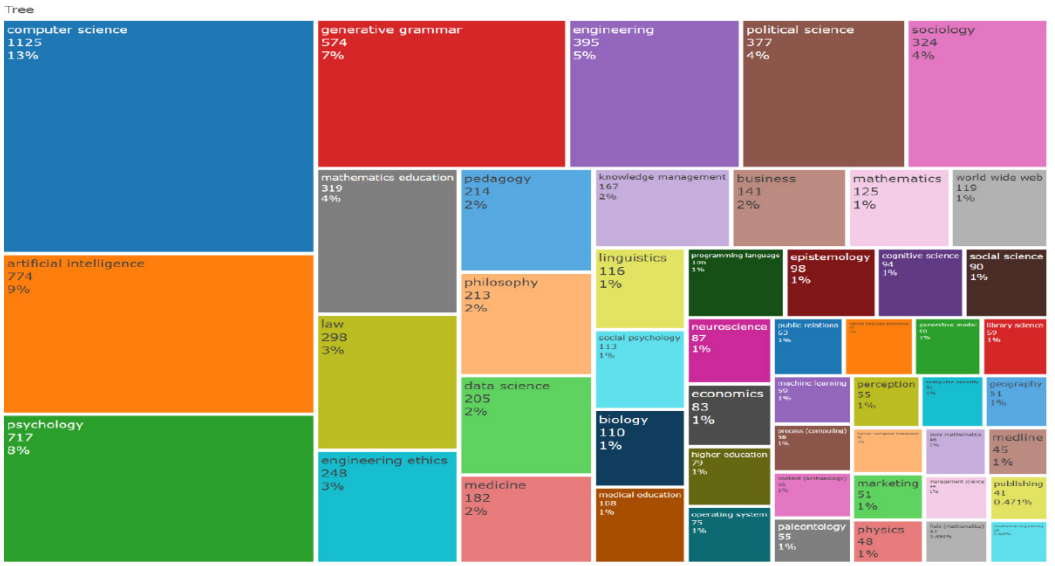

Figure 5

A tree map of 50 most frequently used biogram of research titles

This technique for data visualization uses layered rectangles to show hierarchical data. The area of each rectangle corresponds to the information it illustrates. A tree map of the 50 most frequent bigrams of research titles is plotted in Figure 5. Among these research titles, the term "Computer Science" was seen in most published papers (13% of the documents).The second most published title was artificial intelligent (9%) followed by psychology(8%), generative grammer (7%), engineering (5%), political science (4%), sociology (4%), mathematics education (4%), law (3%), and engineering ethics(3%).

5.8 1 Research hot topic analysis:

Analyzing keyword trends assists in monitoring thematic development and recognizing new research domains. Figure 6 illustrates a consistent increase in author keywords from 2005 to 2025. "Artificial Intelligence" and "Computer Science" display the most significant growth, with Artificial Intelligence slightly edging out Computer Science by 2025. "Psychology" also shows substantial but less pronounced growth, while phrases like "Generative Grammar," "Engineering," and "Political Science" exhibit gradual increases. The yearly frequency plot (2023–2025), based on OpenAlex data, highlights change in median frequency and interquartile range (IQR). Bubble size represents keyword prominence, focusing on the top three (k=3) terms per year. Consistently used terms—such as Computer Science, Artificial Intelligence, and Psychology—indicate stable or expanding

research domains. Short IQR lines suggest steady usage, whereas longer lines reflect fluctuation.

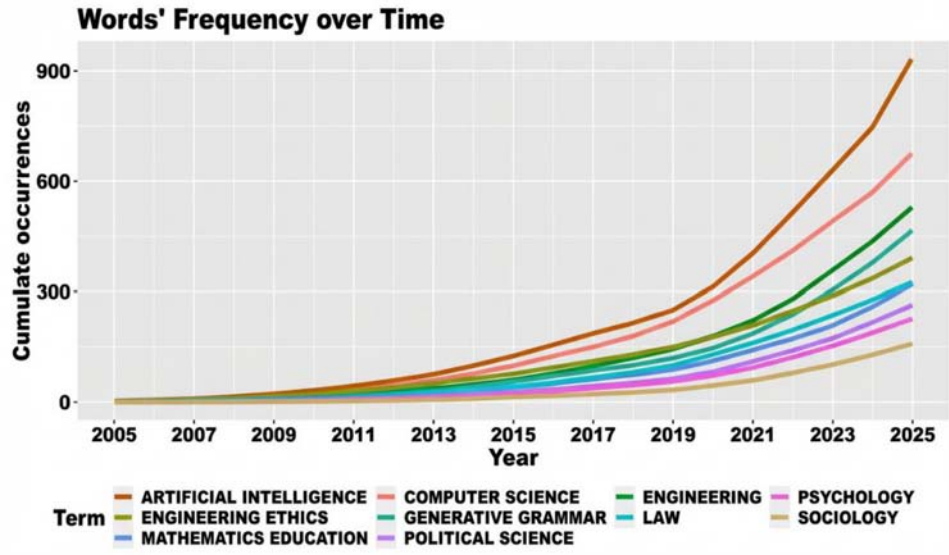

Figure 6

Aword dynamic plot of the most frequent unigram of research titles

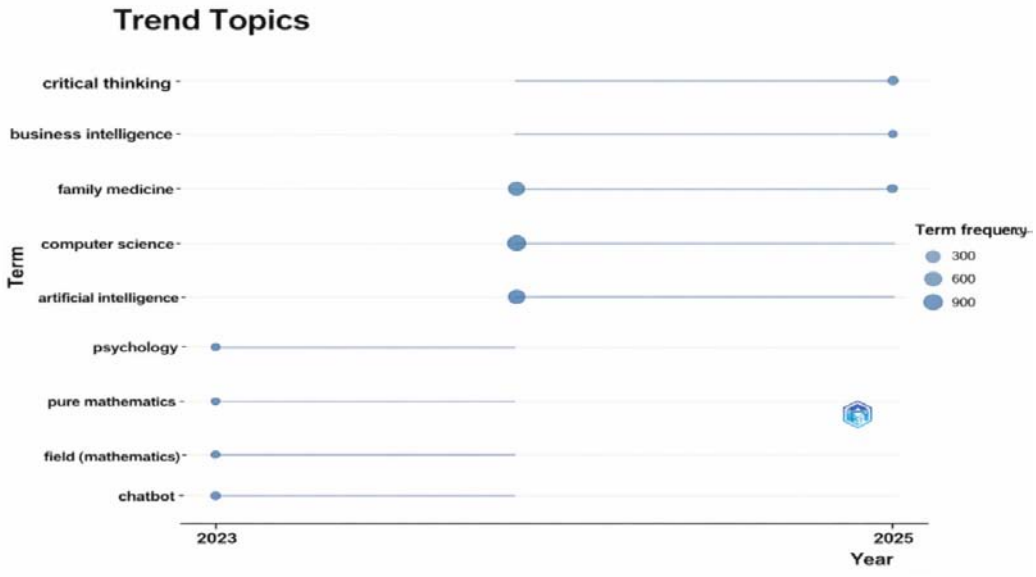

Figure 7

Trend topics identified 2023 to 2025

Emerging themes are also evident. “Chatbot” appears briefly in 2023 before declining, while “Family Medicine,” “Business Intelligence,” and “Critical Thinking” emerge in 2025, indicating shifting research priorities (Figure 7).

5.8 2 Research themes analysis

Figure 8 illustrates how the thematic map was created using the author’s keywords and divided into four themes: emerging or declining (left bottom), motor (top right), niche (left top), and basic themes (right bottom). Motor Themes (High Centrality–High Density, Upper Right): These are well-developed and strongly connected fields that drive the research domain. Political Science, Sociology, Law, Psychology, Education, and Natural Language Processing (NLP) fall within this quadrant. Their position indicates conceptual maturity and strong interdisciplinary integration, making them central to the intellectual structure of the field. Basic Themes (High Centrality–Low Density, Lower Right): These themes are foundational and widely connected but still evolving internally. Computer Science, Artificial Intelligence, and Generative Language belong to this quadrant. Their high centrality confirms their core importance, while lower density suggests ongoing conceptual consolidation and thematic expansion. Niche Themes (Low Centrality–High Density, Upper Left): These are specialized and internally cohesive but relatively isolated from the broader network. Botany, Psychiatry, Clinical Psychology, Ecology, and Open Peer Review represent mature yet peripheral research clusters with limited interdisciplinary integration. Emerging or Declining Themes (Low Centrality–Low Density, Lower Left):

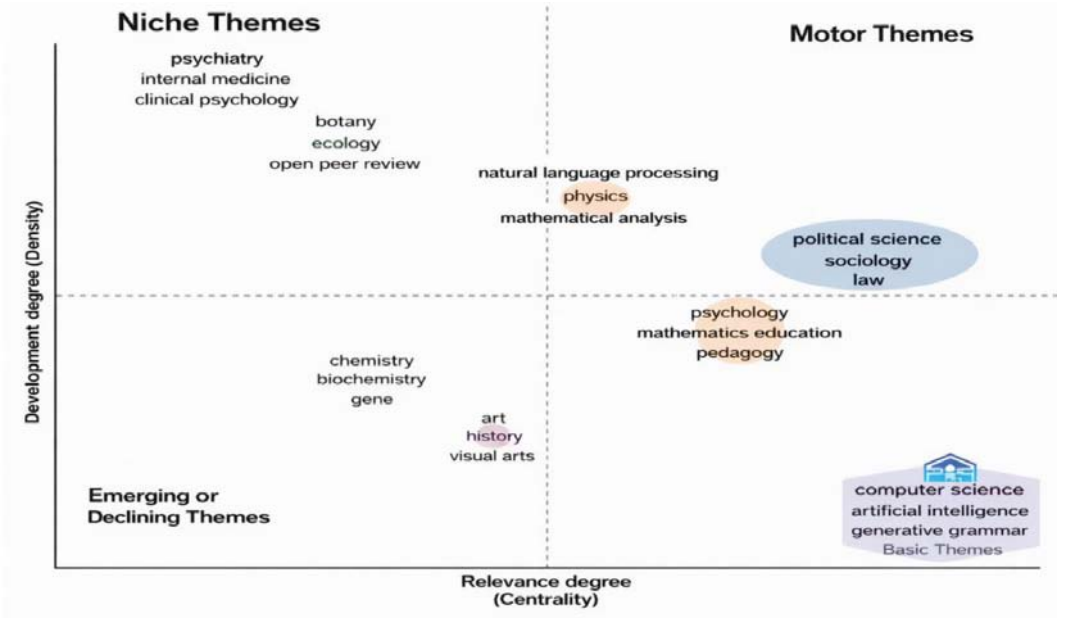

Figure 8

Visualization of thematic mapping

Themes such as Art, History, Visual Arts, Chemistry, Biology, and Genetics appear weakly developed and marginally connected. These areas may represent either nascent research directions or topics losing prominence within the dataset.

The map illustrates a well-structured field: computational and AI-centered themes form the essential core; social science fields function as the intellectual engines; focused medical and ecological research sit on the outskirts; while humanities and natural sciences seem to be either developing or less intertwined with the existing research environment.

5.9 *Countries' Collaboration World Map*

Figure 9 depicts the United States emerges as the leading research hub, marked by the darkest color intensity representing the highest output. Western Europe displays substantial research activity, with several nations shaded darker—countries such as the UK, Germany, France, and Italy likely contribute significantly. China shows a notable volume of research, reflecting its expanding role in global science. In the Southern Hemisphere, Australia stands out as a major research contributor, indicated by its strong color intensity.

The thick web of lines linking countries reflects strong research collaborations, with the United States serving as a central partner in numerous international projects. Within Europe, the dense connections point to particularly strong intra-European cooperation. Significant collaborative ties are evident between North America, Europe, East Asia (especially China), and Australia, underscoring extensive global scientific links. Australia's collaborations are most prominent with the US and China, though it also maintains notable ties with Europe. In contrast, South America and Africa show comparatively weaker connections, highlighting opportunities to expand global research partnerships in these regions.

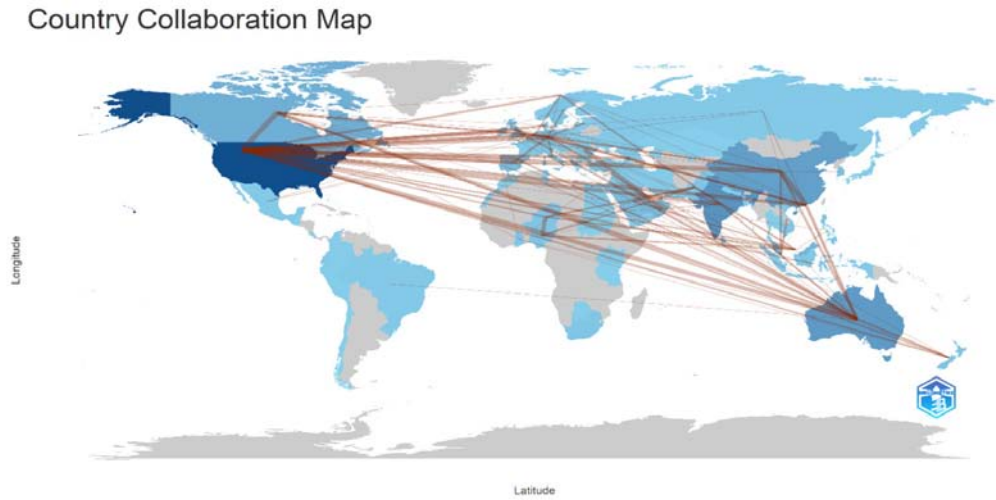

Figure 9

Collaboration world map of data

The United States' leadership in research is likely driven by substantial funding, advanced infrastructure, world-class universities, and a long-standing tradition of global collaboration. China's prominent role reflects its growing investment in science and technology and its deliberate emphasis on building international partnerships, fueling its emergence as a major scientific power. Europe's strong internal links demonstrate the effectiveness of collaborative research initiatives and policies promoted by the European Union. Australia's close ties with the US, Europe, and Asia can be attributed to its strategic geographic position and recognized scientific capabilities.

The map highlights a disproportionate concentration of scientific collaboration in North America, Europe, and parts of Asia. This disparity underscores concerns about research equity and emphasizes the need to foster greater involvement from underrepresented regions, particularly Africa and South America.

5.10 *Co-occurrence of keywords*

The co-occurrence network visualization was created using VOSviewer, featuring 259 keywords associated with Generative AI in scholarly research. A threshold of minimum five (05) occurrences per keyword was established to maintain analytical integrity and thematic significance. The figure 10 illustrates five primary clusters that reflect the intellectual framework of the discipline.

Cluster 1(The Computational Core): This cluster represents the technical engine of the network, dominated by Computer Science and Artificial Intelligence. It encompasses foundational elements like Natural Language Processing (NLP), programming languages, and software engineering. The density of this cluster suggests that AI acts as the primary methodological bridge, connecting data-driven techniques to broader applications in linguistics and automated systems.

Cluster 2 (Business & Data Governance): This cluster, emphasizes business, marketing, and management science, is situated at the nexus of theory and industry. It focusses on the operational side of technology, specifically how Data Science is applied to corporate governance, risk analysis, and economic modeling. The close proximity to the computing core suggests a significant tendency toward "algorithmic business" and the use of data analytics to optimize staff productivity.

Cluster 3 (Socio-Political & Ethical Frameworks): It focuses on the effects of technological progress on humanity, encompassing Political Science, Engineering Ethics, and Social Science. It examines the "boundaries" of innovation, delving into topics such as accountability, inclusivity, and public policy. The significance of "Engineering Ethics" indicates that the research area is growing more concerned with the ethical consequences of AI and the societal obligations of developers.

Cluster 4 (Behavioral Science & Education): This cluster emphasizes human thought processes and teaching methods, grounded in the disciplines of Psychology and Mathematics Education. It examines how information is conveyed and understood, especially in specific areas such as Medical Education and Social Psychology. This cluster

acts as a link between technical fields and human behavior, studying how people engage with intricate systems and educational settings.

Cluster 5 (Life Sciences & Systematic Review): Dedicated to biology, ecology, and evolutionary biology, this cluster is situated on the outskirts. It signifies a more focused area that employs the data tools of the larger network for conducting systematic reviews and publishing peer-reviewed scientific work. Although it continues to be unique, its links to the core indicate a growing dependence on "Big Data" and computational biology for charting natural systems and taxonomies.

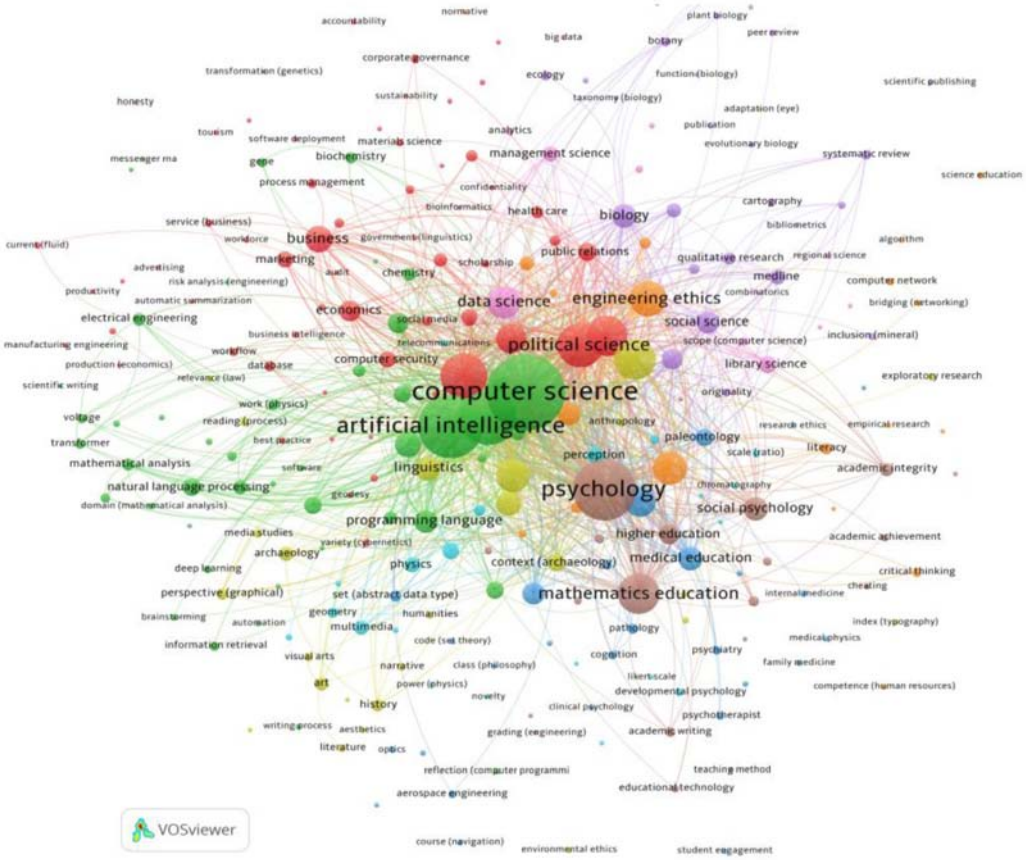

Figure 10

Co-occurrence of all keywords

5.11 *Bibliographic Coupling*

The bibliographic coupling network was built in VOSviewer with a minimum threshold of five documents for each author (Figure 11). A total of 2,430 qualified authors were incorporated, and weak connections were eliminated through a coupling strength filter,

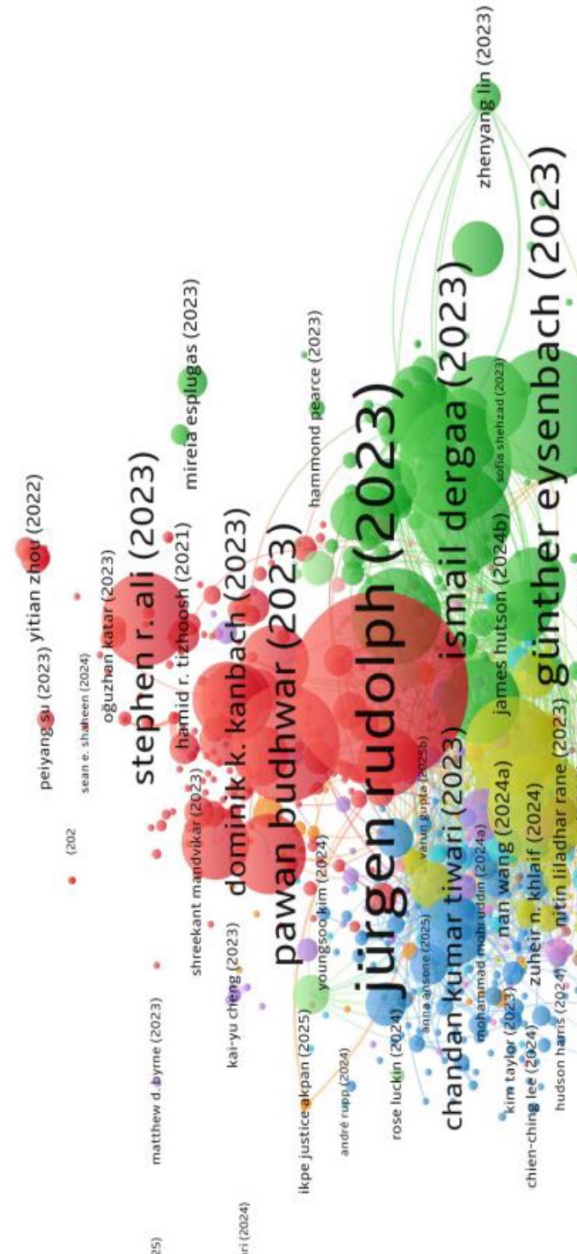

Figure 11
Bibliographic coupling author-based network

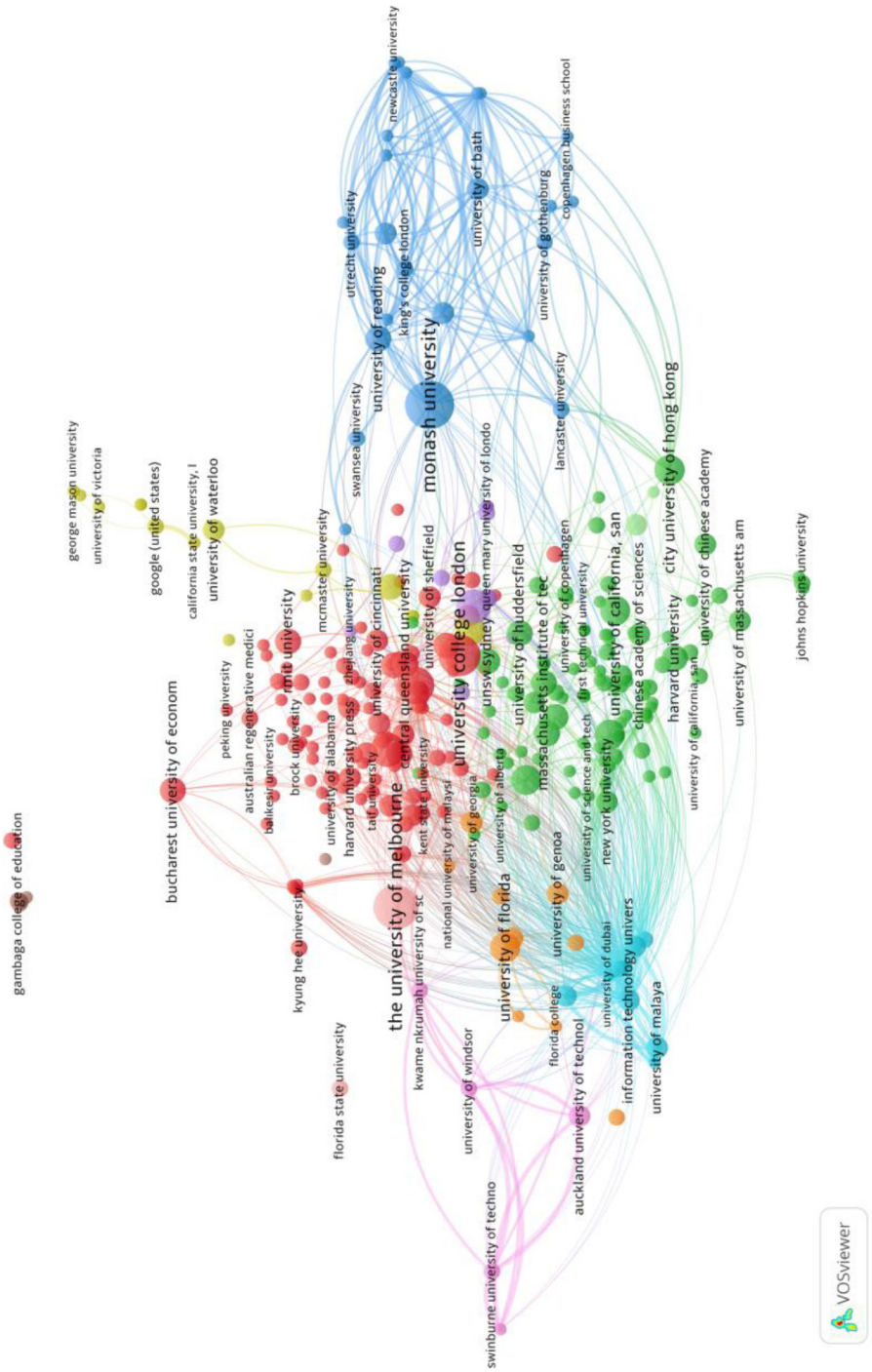

Figure 12

Bibliographic coupling of Institutions publishing in Generative AI in Academic Research

guaranteeing that the network embodies important conceptual associations. The illustration in Figure 12 depicts four distinct author clusters. Cluster 1 (Jürgen Rudolph, Pawan Budhwar, Dominik K. Kanbach, Stephen R. Ali) constitutes the central core, emphasizing themes such as governance, ethics, regulation, and the organizational implications of generative AI. Cluster 2 (Günther Eysenbach, Ismail Dergaa, Zhengyang Lin) focuses on information science, digital scholarship, research integrity, and the role of AI in academic writing. Cluster 3 (Chandan Kumar Tiwari, Ian Wang, Youngjoon Kim) highlights educational uses, particularly the integration of AI in higher education and innovations in teaching methods. Cluster 4 (Cecilia Ka Yuk Chan, Gila Kurtz) explores innovation ecosystems, entrepreneurship, and the transformation of digital business.

The network showcases a well-defined intellectual structure where governance and ethics act as the conceptual core, closely associated with education, information science, and innovation studies—pointing to a swift interdisciplinary consolidation following 2022.

Figure 12 depicts the network of bibliographic coupling among organizations. The nodes represent various institutions, the strength of the links indicates the degree of shared references, and different colors represent specific collaboration clusters. Prominent institutions, such as University College London, Monash University, University of Melbourne, University of Florida, MIT, and Harvard University, show a high level of intellectual interconnectivity.

The observed clustering patterns reveal the structures of regional collaboration. One cluster connects top institutions in the US, UK, and Australia; another primarily showcases European collaboration; a third links US and Asian institutions; while smaller clusters demonstrate selective partnerships, including collaborations between industry and academia.

The map collectively highlights important institutional centers and uncovers collaboration patterns that are organized both regionally and thematically, which shape the intellectual framework of the field.

6. Discussion

Global Research Productivity

The results show that the United States is at the forefront of global research output in Generative AI within academic contexts, driven by its robust funding framework, sophisticated computational resources, research-focused universities, and strong collaboration between academia and industry. The United Kingdom and Australia follow closely, exhibiting ongoing productivity backed by national AI policies and initiatives for digital transformation. Although developed nations dominate this area, there are increasing contributions from middle-income countries, indicating a slow but steady global dissemination, though significant disparities in funding and research capabilities remain.

Conceptual Structure and Thematic Evolution

Analyzing keyword co-occurrences uncovers a multidisciplinary framework rooted in computer science and artificial intelligence, which serve as the field's technical underpinning. Significant connections to psychology, education, ethics, and governance suggest a growing integration across disciplines. New topics—such as academic integrity, critical thinking, accountability, and responsible AI indicate a transition from a focus solely on technology to a research approach that emphasizes social context and governance. The use of methodological terms (e.g., systematic review) indicates a rising level of conceptual and methodological development.

Intellectual Communities and Institutional Structure

Bibliographic coupling based on authors highlights three significant intellectual clusters: (1) management and organizational studies, (2) educational innovation and pedagogy, and (3) health and medical informatics. Key scholars serve as connection points, promoting the exchange of knowledge across disciplines. At the institutional level, top universities in the United States, United Kingdom, and Australia serve as primary centers of knowledge, with robust international connections reflecting organized yet dynamic global cooperation.

International Collaboration Patterns

The country collaboration network displays a core-periphery model. The United States serves as the main hub, linking North America, Europe, East Asia, and Australia. Western Europe shows strong regional integration, while China is rising as a key global player. In contrast, less connectivity in certain areas of Africa and South America reveals disparities in infrastructure, funding, and access to research. Overall, research in Generative AI is becoming more global and interdisciplinary, but continues to be concentrated within established centers of innovation.

The results indicate that, after the release of ChatGPT, academics need to merge technical skills with ethical understanding, openness, and AI literacy to promote responsible research methodologies. Educational institutions should allocate resources towards interdisciplinary AI systems and create definitive governance structures to oversee AI-enhanced teaching and research. Additionally, funding organizations should back collaborative efforts that encompass diverse, international perspectives while ensuring a balance between technological progress and ethical, educational, and social factors.

7. Conclusions

This scientometric assessment of 1,329 publications indexed by OpenAlex (from 2005 to 2025) shows a swift growth in Generative AI research within academic context, characterized by a substantial annual growth rate of 36.01% and consistent citation impact. Although the United States holds the highest total citations, nations like France and Poland demonstrate

a greater average citation impact, highlighting the difference between the volume of research and its overall influence. Thematic and network analyses illustrate a multidisciplinary framework rooted in computer science and artificial intelligence, with an increasing incorporation of education, psychology, law, and governance, suggesting a shift from technology-focused studies to research that is socially embedded and policy-driven.

Despite its contributions, the research is constrained by depending on single database (OpenAlex) and publications in English. Upcoming studies should involve comparative analyses of different databases, AI-based predictive scientometric models, and qualitative analyses of networks to gain a deeper insight into intellectual integration and global inequalities. Enhancing ethical governance structures, fostering interdisciplinary collaboration, and establishing inclusive funding strategies will be crucial for promoting responsible and globally equitable development in Generative AI in academic research.

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