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SURVEY

Exploring Generative Artificial Intelligence Research: A Bibliometric Analysis Approach

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ABSTRACT Artificial Intelligence (AI) and its many applications are changing our lives in ways we could not have imagined a decade ago. Generative artificial intelligence is an artificial intelligence system capable of generating texts, images, and other media based on the input training data. Although still in their early stages, numerous examples of such systems in different domains have gained widespread attention from the public, media, policymakers, and researchers. This study aims to explore the generative AI academic research in the past decade using bibliometrics, text analysis, and social network analysis. Specifically, research themes and their relationships, the evolution of research themes over time, and prominent authors, articles, journals, institutions, and countries publishing in generative AI are identified. The data was further found to partially support the classical bibliometrics laws of Zipf, and Bradford's. The two overarching research themes identified using knowledge synthesis from most cited articles and journals are technical advancements and developments in generative AI systems; and their applications to image processing, pattern recognition, and computer vision. ChatGPT, large language models, and the application of generative AI to healthcare and education are emerging research topics. Additionally, generative AI's usefulness to geoscience, remote sensing, Internet of Things (IoT), and cybersecurity are discussed.

INDEX TERMS Generative artificial intelligence, bibliometric analysis.

I. INTRODUCTION

Artificial Intelligence (AI), a term first coined by John McCarthy in the 1950s, "is the science and engineering of making intelligent machines" [1]. With recent advancements in artificial intelligence and its applications, our society faces growing technological, legal, and ethical concerns at different levels in various contextual scenarios. What was started in the 1940s and 1950s is now believed by many to be the tipping point of artificial intelligence research, leading towards the development of Artificial General Intelligence systems capable of mimicking human behavior, emotions, and intelligence [2]. Generative artificial intelligence is a recent development gaining widespread attention from individuals, society, and governments worldwide due to its applications to tasks usually under human expertise. Generative AI systems, in general, are defined as AI systems capable of generating new data based on the input training data. These newly generated data can be in the form of text (for instance, ChatGPT from OpenAI [3] and Bard from Google based on its large language model LaMDA [4]), images and arts (DALL-E 2 from OpenAI [5]), music (MusicLM from Google [6]), programming code (GitHub's Copilot powered by OpenAI's Codex [7] and AlphaCode by Google's DeepMind [8], video (Meta's Make-A-Video [9]), and synthetic data [10], to name a few.

These systems are the outcome of continued research and developments in AI, starting from the Hidden Markov Models and Gaussian Mixture Models in the 1950s to Natural Language Processing, deep neural networks, and computer vision in later decades, and finally, Generative Adversarial Networks or GANs in the mid-2010s [2], [11], [12]. Although widespread adoption of these systems is yet to be seen, their limited use, especially those capable of generating text (such as ChatGPT), has already alarmed researchers and policymakers, as well as legal and ethical experts, due

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to many underlying issues [13], [14]. Notable examples that got generative AI applications into hot waters include winning an Art prize for an AI-generated picture [15] and intellectual property issues [16]. Despite these challenges, organizations are realizing the potential of generative AI and are embracing it. For instance, Microsoft and Google have added generative AI capabilities to their respective search engines, IBM included generative AI to its Watson platform, and consulting firms such as McKinsey, Ernst & Young, and PricewaterhouseCoopers made huge potential investments in generative AI technologies [17].

The academic community has published an increasing number of research articles on generative AI, particularly after 2013, to keep up with and complement the above technological advancements from the industry. This trend of increasing number of publications over the past decade is shown in Figure 1. It must be noted that, although many of these articles are technical, others also attempt to address numerous research problems involving applications of generative AI to different disciplines and industries. With ever-increasing knowledge latent within these scholarly articles, it is imperative that we must comprehend underlying themes, disciplinary boundaries, research traditions, and important research constituents (authors, articles, journals, institutions, and countries). This is per research scholars studying the evolution of their discipline. Systematic literature reviews, meta-analyses, and bibliometric analysis studies are commonly used methodologies for such studies aimed toward understanding the existing knowledge and its limitations. Examples include systematic literature reviews in software engineering [18] and smart cities [19], meta-analysis studies on the effectiveness of computer applications [20] and computer gaming for learning [21], and bibliometric studies on computer networking research [22] and applied soft computing [23], among others.

Since, the goal of our research is to present "the state of the intellectual structure and emerging trends" of generative AI research, by using a large dataset of article corpus, bibliometric analysis is chosen over systematic literature reviews or meta-analysis [24]. Although there have been a few published review articles in this domain (for instance, [25], [26], [27]), concentrating on the specific applications of generative AI such as in education, healthcare, or across industries [28], to the best of our knowledge, none of them looked into the scholarly structure and evolution of generative AI scholarly research itself. Therefore, this study aims to address this research gap by employing bibliometric analytic approaches [24] to examine the intellectual structure of generative AI academic research during the last ten years. Accordingly, the following research questions are addressed in this study:

- What are the underlying research themes or knowledge areas? How the knowledge areas are related? These relationships are based on the bibliometric connections (or connections based on citations) between the published research. This will not only allow us to explore the current state of academic research in this area but also help scholars looking to publish in the future.
- How has the generative AI discipline evolved over the past decade concerning the above knowledge areas? This research question is aimed at understanding the progression of academic research.
- Who are the influential research constituents (authors, articles, journals, institutions, and countries)? This will allow us to identify the important contributors.

The research articles indexed in the Web of Science's core collection database over last ten years (2013 - 2024) are analyzed using techniques of citation analysis, article co-citation, journal co-citation, social network analysis, author keyword analysis, and co-word network of author keywords to answer the above research questions.

The remainder of the paper is structured as follows. The next section describes the data collection followed by a brief overview of bibliometric analysis methodology used in this study. A discussion of findings from bibliometric analysis, text analysis, and social network analysis follows. The research themes are identified, and the progression of thematic areas is briefly discussed in this section, followed by identifying prominent research contributors. The second-to-last section discusses a few noteworthy disciplines and examples where generative AI tools and techniques are used. This section also summarizes the findings of our study, followed by conclusions and future research directions, in the last section.

II. METHODOLOGY

A. DATA COLLECTION

The Web of Science core collection database for research articles is used to retrieve the bibliometric data used in this study. Although there are other scholarly databases, such as Scopus, Dimensions, and Google Scholar, which were used in the past for survey research, the citation indexes (Science Citation Indexes Expanded, Social Science Citation Index, and Arts & Humanities Citation Index) from Web of Science is not only the oldest and well-known but also widely used in the academia for bibliometric and meta-analysis studies [29], [30], [31]. The ease with which bibliometric data can be downloaded either as a text or Excel file and imported into citation analysis software (such as VOSviewer [32], which is used in this research) for further analysis is another reason behind using Web of Science. The topic search, which includes searching for the keywords within article title, abstract, author keyword, and keyword plus (index terms generated from titles of cited articles) is performed using the keywords for generative AI research identified based on published academic literature. Only journal articles published in the English language are used. Quotation marks to search for the exact keyword phrases and the OR logical operator are further used to formulate the search query. Figure 2 shows the data collection process.

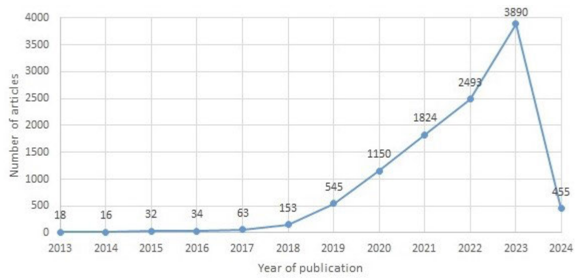


FIGURE 1. Generative AI publications trend in recent years.

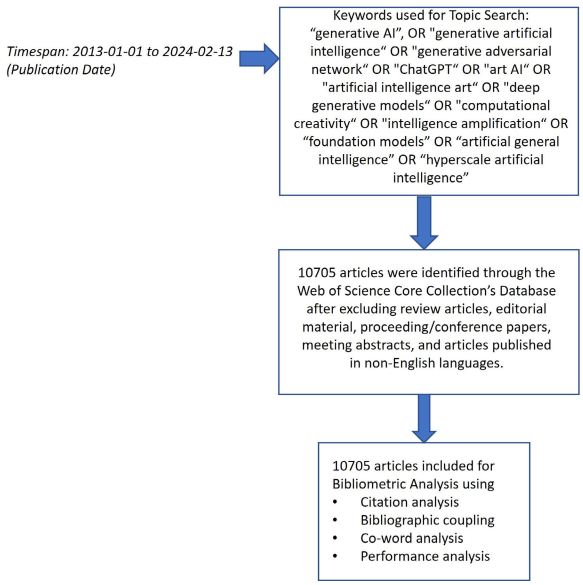


FIGURE 2. Relevant articles selection.

B. BIBLIOMETRIC ANALYSIS

Bibliometric analysis techniques such as citation analysis, co-word analysis, performance analysis, and network analysis are aimed at investigating and analyzing scholarly data [24]. Studies based on bibliometrics aim to discover the intellectual structure of a scientific discipline or a specific journal. Bibliometrics often also includes quantitative analysis of the performance of the research constituents to find the most productive or influential authors, articles, journals, institutions, etc. In this regard, bibliometrics is similar to scientometrics, which involves studying the "growth, structure, interrelationships, and productivity" of a scientific discipline [33]. There has been a recent surge in bibliometric analysis studies due to the availability of scientific data from databases such as Web of Science's core collection's citation index and Scopus's citation database. The data from these scientific databases can easily be downloaded as text or Excel files, along with other formats [34]. These databases contain information from thousands of scholarly journals, conference proceedings, books, etc. Once downloaded, the scientific data can be analyzed using specialized software for bibliometrics, many of which are open source and equipped with advanced visualization capabilities [35]. Bibexcel [36], CiteSpace [37], VOSviewer [38], and Sci2 [39] are among the favored software for carrying out bibliometric analysis. Apart from such specialized software, general-purpose programming languages such as Python [40] and R [41] also include libraries for analyzing scientific literature data. For this study, Microsoft Excel is used to plot the publication trend, identifying the prominent (and most cited) journals, top author keywords (including author keyword distribution and author keywords over the years), author-article distribution, prominent institutions, and top funding agencies. These plots were generated using Excel capabilities such as VLOOKUP, Pivot tables, and in-built Excel functions, which were applied to the raw data representing generative AI academic research downloaded from the Web of Science citation database. VOSviewer is a software tool for visualizing scientific landscapes, which is used for bibliometric analysis, and R is used for social network analysis.

Researchers in the past have used bibliometric analysis techniques to uncover the intellectual structure of specific journals such as the European Journal of Marketing [42], the Journal of Business Research [43], and the International Journal of Information Management [44], among others. Apart from scientific journals, bibliometric analysis techniques have also been used to explore the trends and intellectual structure of scientific disciplines such as knowledge management [45], artificial intelligence in healthcare [46], AI and big data in information systems discipline [47], and operations research and management science [48], to name a few.

Apart from using the bibliometric analysis techniques, we also carried out the exploratory analysis of the data from the perspective of various well-known bibliometrics laws such as Price's law [49], Zipf law [50], and Bradford Law of Scatter [51]. These laws are well-established in informetrics, bibliometrics, and scientometrics and have been used by scholars to verify the trend of publications within their respective fields. Of these laws, Zipf's law is the most popular and found application in many fields [52].

III. ANALYSIS AND FINDINGS

The average number of articles published per year is 889.42. This average is 52.67 for the first six years and 1,726.17 for the next six (till February 2024). Thus, most articles within our corpus were published after 2018, with an increasing trend in recent years, as shown in Figure 1. Note that since 2024 is still an ongoing year, there is an apparent dip in the number of articles. Our article corpus includes 50,516 authors, of which 37,298 are unique. Price's square root law states that "half of the literature on a subject will be contributed by the square root of the total number of authors publishing in that area" [53]. Hence, as per this law, half of the articles within our corpus, i.e., 5353, must be produced by the square root of the number of unique authors, i.e., 193. However, our data does not support this theoretical implication, where 5353 articles were published by many (top 676 authors). This finding is not surprising as similar

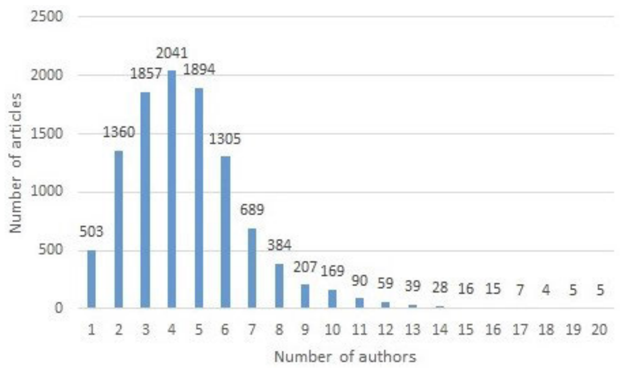


FIGURE 3. Authors and articles.

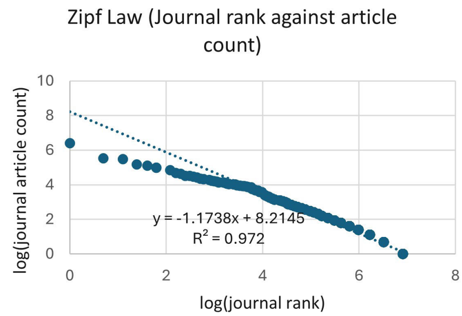


FIGURE 4. Zipf Law verification for journal rank versus the number of published articles.

studies in the past did not find empirical support for Price's law [53], [54].

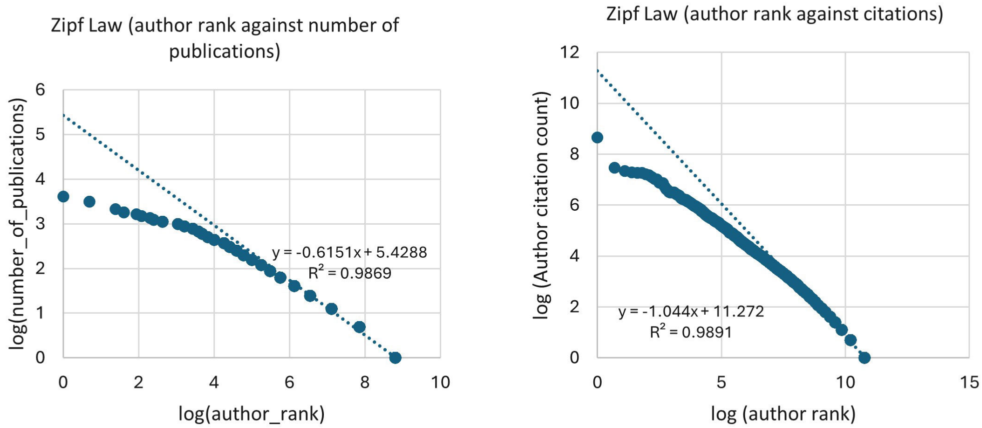
Within our article corpus, articles with four authors are the most common (n = 2,041). The distribution of the number of authors by number of articles is shown in Figure 3. There are 503 single-author papers, and 326 is the greatest number of authors on a single paper. Although negative binomial regression analysis (as advocated in similar studies [44], [55]) with author count as an independent variable, and citations received by an article as a dependent variable shows a positive and statistically significant relationship (p-value $\ll 0.05$), exclusion of other variables (such as author affiliation institute, reputation of the author, article length, number of references, etc.) warrants further analysis and is left out as one of the research questions to be addressed during future extension of the current study.

There has been an apparent increase in the number of articles since 2014. The year 2014 was historically important in generative AI, marked by the publishing of a few seminal articles aimed towards the development of what came to be known as Large Language Models or LLMs(for instance, see [56], [57]). These models aim to understand the meaning of the words based on contextual information. Interestingly, the year 2014 also saw the launch of Alexa, a successful smart speaker capable of speech recognition, processing, and responding to natural human language from Amazon, and the passing of the Turing test by a chatbot named Eugene Goostman [58]. The year 2015 was similarly remarkable for the generative AI community with the founding of OpenAI and its research on generative models, which subsequently resulted in the development of a well-publicized chatbot named ChatGPT [59]. All these developments further fueled a growing interest of researchers working in this area. Gartner, a technology consulting firm that publishes an annual hype cycle, puts generative AI as one of the technologies with a "peak of inflated expectations" for 2023 [60].

Based on a preliminary analysis of the article corpus, the research articles within our corpus were published in 2,065 journals. IEEE Access is the most prominent journal, with 599 articles, followed by Sensors (249 articles) and Applied Sciences (237 articles). Hence, the popularity or ranking of a journal for a scientific discipline can be measured based on the number of articles published by that journal. We can verify the journal's publishing trend using Zipf law. Zipf law, first proposed by the linguist George Kingsley Zipf, states that the frequency of a word for a given corpus of text is inversely proportional to its rank in the frequency distribution table for all words in the corpus [61]. This law has since been applied to many contextual scenarios [52], including bibliometrics [62]. The log-log plot with the journal rank on the x-axis and the number of articles on the y-axis is shown in Figure 4. This graph shows that our data loosely follows Zipf law (as the slope is close to minus 1), especially for the lower-ranked journals. The high R-squared value also shows that the trend line fits the data well and can explain most variance. We further found that our data partially supports Zipf law when applied to the author's rank against the publications and citation counts as shown in Figure 5. Similar support is also found for other data attributes such as cited references, institutions, countries, and funding agencies as depicted in Figure 6. The top 10 journals publishing generative AI research with a minimum total article count greater than 100 over the years are further shown in Figure 7.

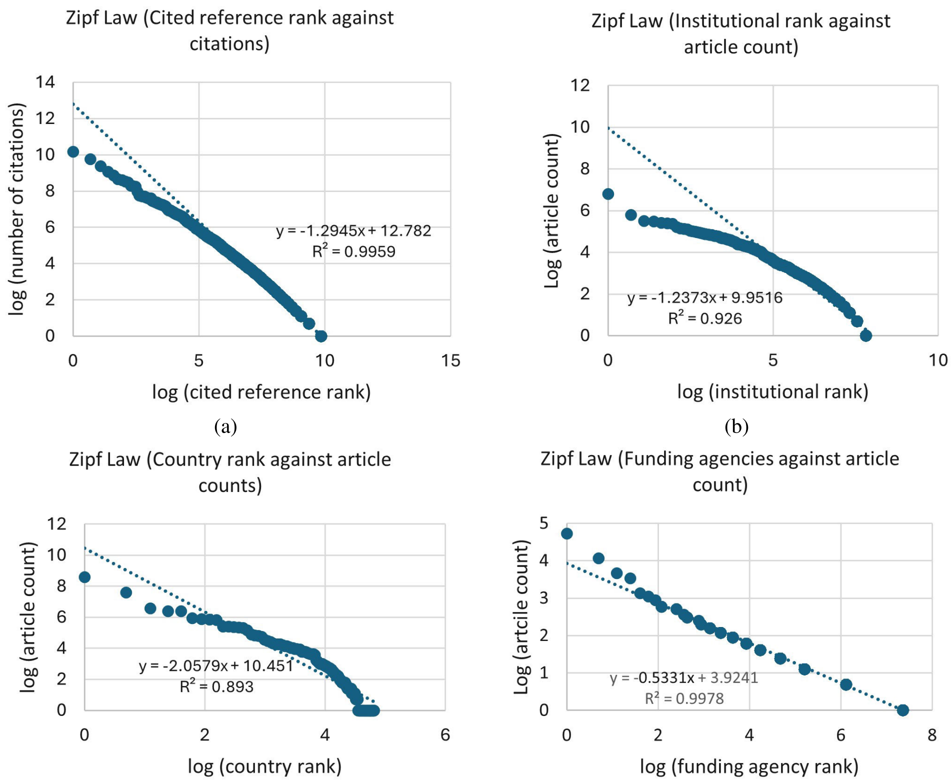
A. UNDERLYING RESEARCH THEMES

The intellectual structure of a scientific discipline involves identifying clusters or groups representative of the underlying thematic areas [63]. Historically, citation analysis [64], author co-citation analysis [65], [66], social network analysis [67], bibliographic coupling [68], and co-word analysis [69] were the commonly used techniques to extract the underlying research themes from the article corpus. The unit of analysis for such studies is either authors, articles, or journals. In this study, we have used co-citation analysis on articles and journals to extract the themes latent in the corpus. Co-citation is "the frequency with which two documents are cited together" [70]. Using co-citation analysis, clusters of documents or authors that are cited together provide a means to study the intellectual structure of a scientific discipline. Studies in the past have used author co-citation [65], [71] and document co-citation [72].



(a) (b)

FIGURE 5. **Zipf Law verification for author rank versus number of publications and citations.**



(a) (b) (c) (d)

FIGURE 6. **Zipf Law verification for cited references, institutions, countries, and funding agencies.**

The 4 article clusters using co-citation analysis of articles based on cited references are shown in Figure 8. These article clusters and their relationships are derived using the VOSviewer software tool. Here, the top 100 articles with a minimum citation count of 153 are used to develop clusters representative of the underlying research themes. The size of the node and label is representative of the citation count received by the article, nodes with the same color belong to the same cluster, links between articles are representative of co-citations, and closeness of nodes/articles represents their relatedness in terms of co-citation links [32]. A brief description of the four clusters based on the article titles follows. These descriptions are based on synthesizing the knowledge inherent in the article titles, author keywords, article abstracts, and in some cases complete articles. The goal of this process is to come up with a common research theme or knowledge area representative of articles that are part of the same cluster.

Cluster 1: This cluster includes articles representative of technical developments within generative AI. More specifically, this cluster includes research on generative adversarial networks (GAN) and conditional GAN, construction of classifiers from imbalanced datasets, GAN-based medical imaging, deep learning, deep CNN and deep convolutional GAN, training of deep networks and GANs, reducing the dimensionality of data with neural networks, long-short term memory, document recognition, conditional image synthesis, transfer learning, preventing neural networks from overfitting, visualizing data using t-SNE, and transformer neural network. Apart from these, few articles within this cluster represents research on image classification, AI-assisted medical education using large language models, and Python programming language's PyTorch library for deep learning.

Cluster 2: Cluster 2 includes articles representative of applications of generative AI to image synthesis and image-to-image translation research. More specifically articles within this cluster include research on image style transfer, detection of facial attributes, feature learning in images, and computer vision.

Cluster 3: Cluster 3 mainly includes articles representative of research involving image super-resolution. Some of the topics addressed by articles published within this cluster include deep convolutional networks for image super-resolution, real-time style transfer of images, photo-realistic image super-resolution, image quality assessment, and image denoising including CT images.

Cluster 4: Cluster 4 is representative of research involving image segmentation and image recognition. Important research topics addressed within this group are semantic image segmentation, deep residual learning for image recognition, object detection in images within contexts, real-time object detection, and biomedical image segmentation.

In summary, the first cluster includes research articles focused on GAN, deep learning and CNN. The second cluster addresses the image synthesis, image-to-image translation, and computer vision. Cluster 3 involves research addressing image super-resolution and image quality. Finally, cluster 4 represents image segmentation and recognition using CNN and GAN.

The top 20 cited journals and conferences are shown in Figure 9. It is interesting to observe that some of these journals belong to the disciplines of medical imaging, Geoscience, and medical physics, suggesting the usefulness of generative AI in addressing research problems inherent in these fields. The presence of these journals as an important knowledge source for domain-specific generative AI research is further corroborated by the findings from the journal co-citation network, as explained below.

The co-citation network using the VOSviewer software for the top 100 journals and conferences (minimum citation count = 529) provides further insights into the underlying research themes based on journal clusters, as shown in Figure 10. Research on computer vision and graphics, pattern recognition and image processing, artificial intelligence, neural information processing, and machine learning are prominent among the clusters. Application of these techniques to geosciences, remote sensing, clinical medicine, biology, biochemistry, biomedical, and health informatics results in the emergence of other clusters within the corpus.

The most frequently used author keywords and terms in the article title also provide us a glimpse into the prominent research topics. These are shown in Table 1. Many research articles are based on training and design of GAN and deep generative model. Generator training, anomaly detection, transfer learning, and fault diagnosis are relevant to optimizing generative AI systems. Image synthesis, translation, reconstruction, super-resolution, enhancement, segmentation, and reconstruction are sub-topics of image processing research using deep neural networks, CNNs, and GANs. Machine learning, artificial intelligence, feature extraction, task analysis, generative model, and computational creativity represent overarching research in this area. Simulation and survey are standard research methodologies, and a recent surge in research based on ChatGPT is evident from the article corpus.

B. EVOLUTION OF RESEARCH THEMES

Natural language processing techniques aimed at exploring the trends in the usage of author keywords over the entire article corpus and overlay visualization of the co-word network of terms occurring in article titles over the past few years (2016 – 2024) are carried out to answer the second research question concerning the research trends. Author keywords are used in similar studies to explore the evolution of research themes for a scientific discipline (for instance, see [73]). Similarly, co-word analysis and co-word network visualizations are also used, for instance, to study the evolution of specific scientific areas such as software engineering [74], and the Sarbanes-Oxley Act-related Research within IS [75], or to understand the patterns of publications within a specific journal [76].

There are 57,802 author keywords for the 10,705 articles. These keywords are used directly from the articles within our corpus. The average number of keywords is 5.39 per article. Of these, 22,413 are unique author keywords. The frequency distribution of author keyword counts over the years is shown in Figure 11. Similar to the increase in the number of articles in recent years, there is an apparent increase in the number of author keywords, with the majority of them used after 2018 (56,323 of 57,802 or 97.44%).

The frequency distribution for prominent author keywords having a minimum frequency count of 100, over the years is shown in Table 2. The right-most column in this table shows the total count for the respective author keywords. For instance, computational creativity is used 131 times as an author keyword within the corpus. Generative Adversarial

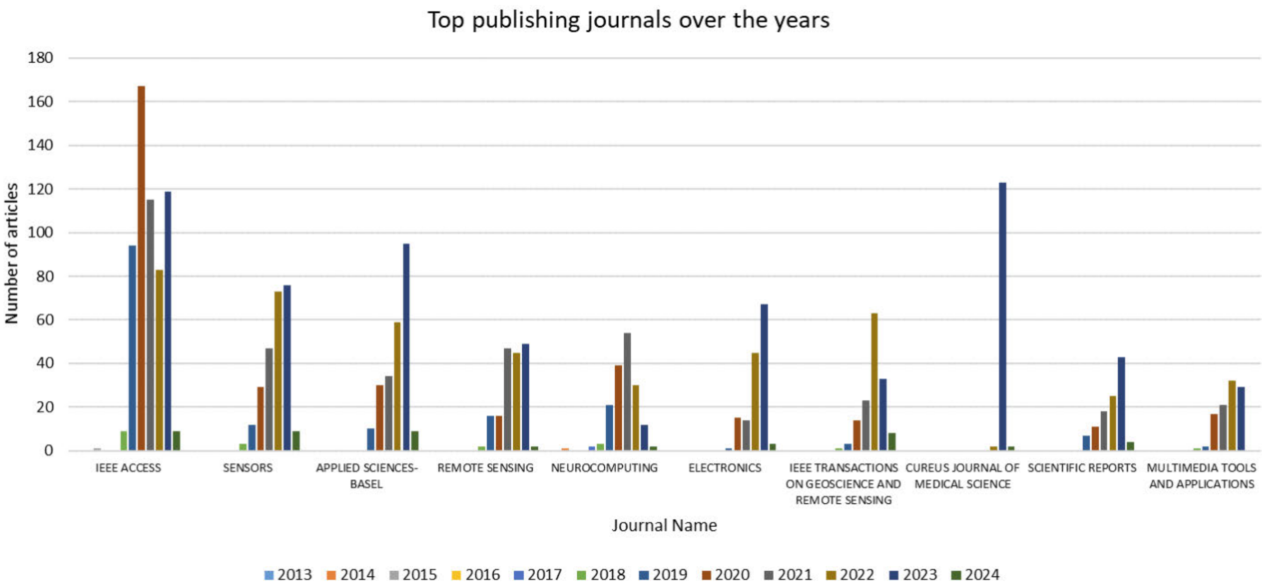


FIGURE 7. Prominent journals publishing generative AI research over the years.

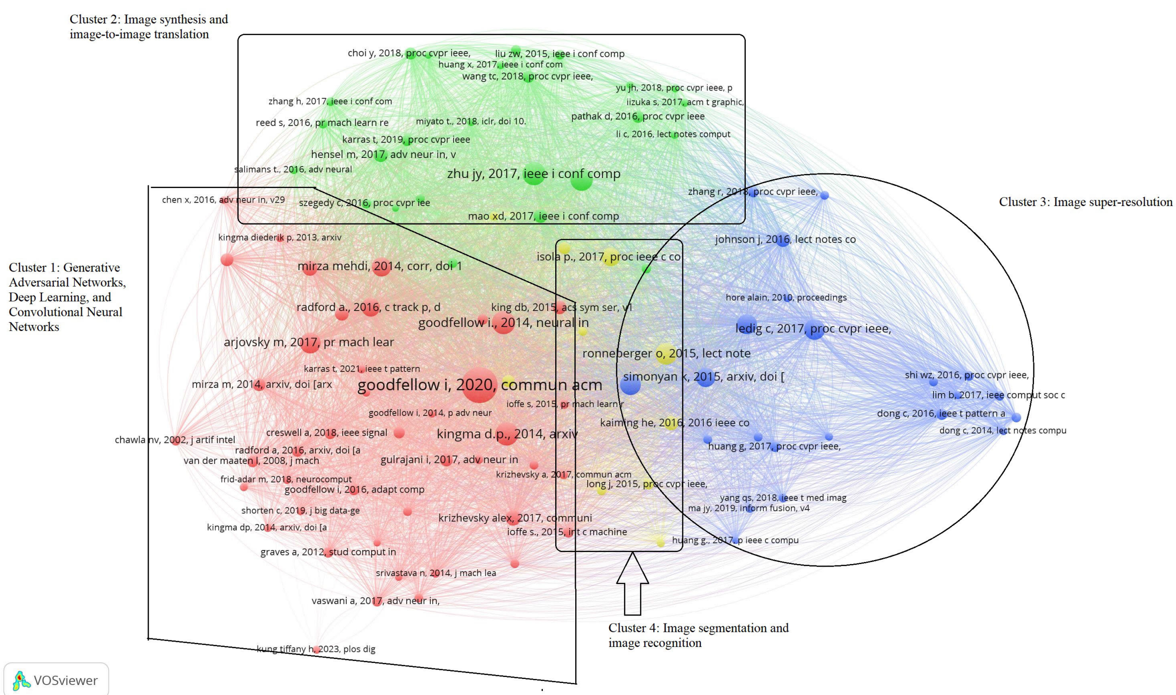


FIGURE 8. Identifying research themes using article co-citation.

Network or GAN (n = 4,445), deep learning (n = 1,558), and training (n = 561) are the top three author keywords. Interestingly, artificial intelligence and computational creativity are the author keywords used throughout the article corpus, starting from 2013. Computational creativity is a sub-field of AI, aiming towards studying computational systems capable of exhibiting creative behaviors [77]. Notably, there's a growing interest of not only researchers in developing such systems but also individuals in using such systems for creative writing, music generation, arts creation, etc.

Co-word analysis is a quantitative knowledge discovery technique to understand the interrelationships between scientific disciplines and subjects within a research field [78]. The word co-occurrence overlay visualization network for

TABLE 1. Top author keywords and top terms used in article titles.

Author Keyword (count)	Terms used in article title (count)
generative adversarial network (n=5404)	generative adversarial network (n=3492)
deep learning (n=1911)	image (n=734)
Artificial intelligence (n=789)	chatgpt (n=679)
ChatGPT (n=707)	detection (n=620)
Training (n=648)	network (n=554)
Generators (n=546)	generation (n=396)
Machine learning (n=468)	classification (n=384)
Feature extraction (n=449)	prediction (n=357)
data augmentation (n=350)	deep learning (n=299)
Task analysis (n=330)	framework (n=280)
convolutional neural network (n=252)	conditional generative adversarial network (n=260)
Data models (n=248)	recognition (n=256)
Image reconstruction (n=235)	synthesis (n=250)
Anomaly detection (n=176)	segmentation (n=249)
Transfer learning (n=156)	analysis (n=236)
Neural networks (n=155)	artificial intelligence (n=234)
attention mechanism (n=154)	reconstruction (n=234)
remote sensing (n=150)	super resolution (n=210)

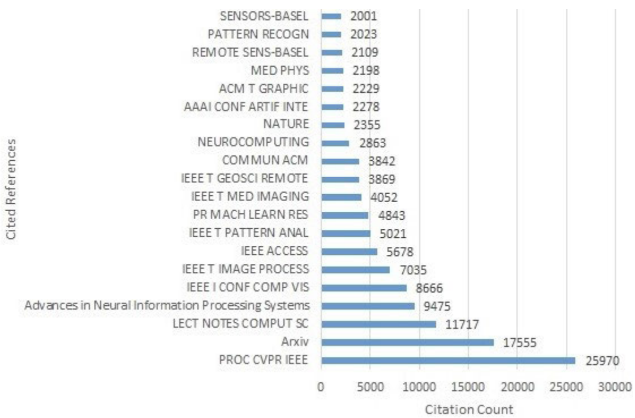


FIGURE 9. Top cited journals and conferences.

terms occurring within article titles for the years 2020 to 2024 (until 13 February 2024, when the data was collected) is shown in Figure 12. Note that although the timeline for data collection is 2013 to 2024, only the years 2020 and later are used here, as these years show the most variability concerning the usage of terms in article titles. Here, the top 100 most relevant keywords (based on a relevance score from VOSViewer software) with a minimum frequency count of 25 are used. The node color represents the average year for a term to be used in an article title. For example, the average publication year for the deep learning is 2021.74, while 2023.14 for chatGPT. Hence, we can explore the evolution of generative AI research over the past few years based on the average usage of the most prominent terms by researchers within article titles.

Artificial General Intelligence is a term prominently used before 2021. The first half of the year 2021 saw image processing research focused on image segmentation, classification, recognition, and super-resolution. Transfer learning, deep neural networks, and convolutional neural networks were other prominent topics of interest, while the second half of 2012 was more focused on topics such as Generative Adversarial Networks (GAN), conditional GAN, Wasserstein GAN, cycle GAN, anomaly detection, fault diagnosis, data augmentation, COVID, deep generative models, image generation, image reconstruction, prediction, framework, algorithm, and MRI. Image enhancement, artificial intelligence, transformer, patient, accuracy, study, assessment, performance, survey research, opportunity, and challenge are terms within article titles from 2022. Finally, 2023 and early 2024 saw a prevalence of terms such as Generative Artificial Intelligence, GPT, chatGPT, large language models, and education within article titles.

C. SOCIAL NETWORK ANALYSIS

Studying scientific collaboration between authors has been an active area of research in the past [79], with co-authorship networks being a popular technique to study such collaborations [80], [81]. Within the co-authorship network, authors are represented as nodes and their co-authorship relationships as degrees. The degree distribution for the nodes is shown in Figure 13. The majority of nodes having a degree of 1 and the density of the network being 0.000066 suggests the network to be sparse in nature. The average path length or mean distance of the network is 1.6532. The overall network having a small mean distance is further reflected in the closeness centrality measure of 1 for many nodes/authors, as shown in Table 3. Network assortativity is positive with a value of 0.21246. Assortativity is often used as a measure of homophily in co-authorship networks [82]. This value being positive, although indicates authors with similar attributes or characteristics (for instance, age, gender, experience, etc.), having more probability towards collaboration, the magnitude being close to zero (rather than 1), does not provide a strong indication towards this phenomenon of assortativity [83].

Centrality measures have been used in the past in the context of analyzing co-authorship networks to measure

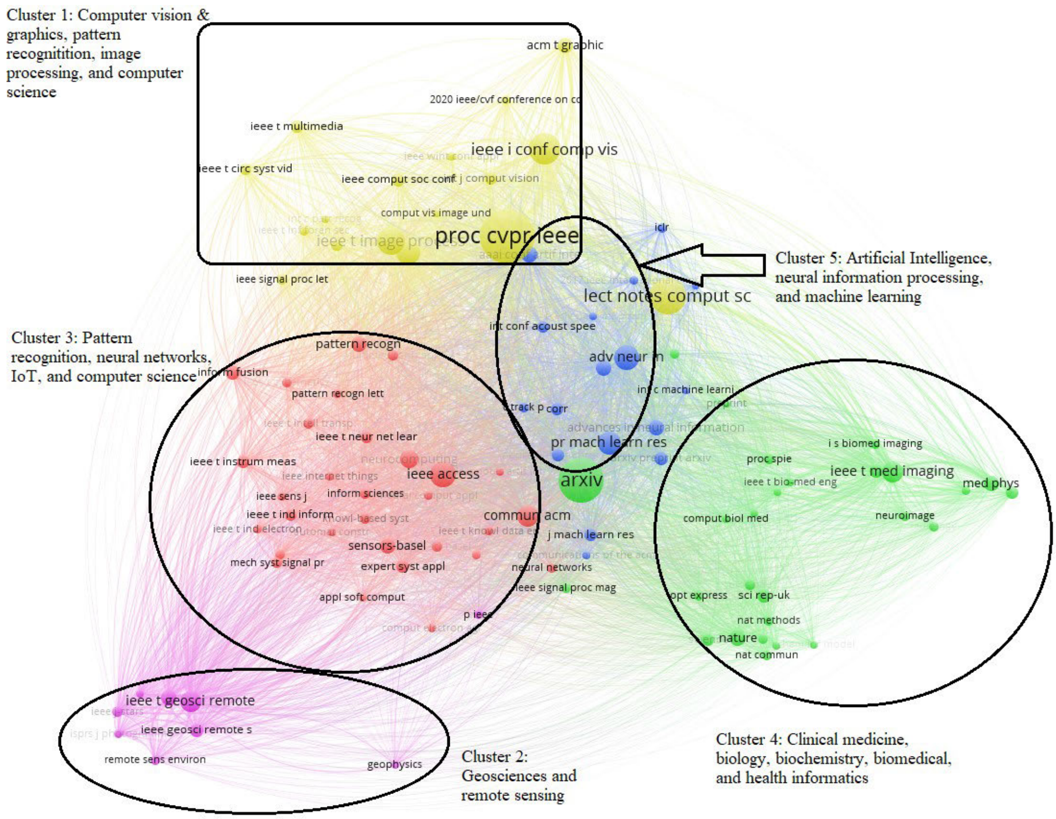


FIGURE 10. Identifying research themes using journal co-citation.

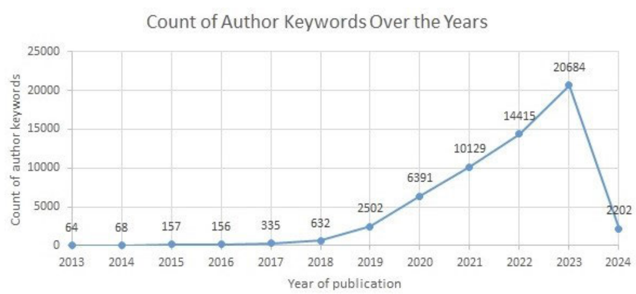


FIGURE 11. Author keyword yearly distribution.

the relative importance of the position of authors within a social network [84], [85]. Degree centrality measures the number of links or connections for a node (author in our case). Betweenness centrality measures the number of times a node lies on the shortest path between any two nodes within the network. In other words, it shows the bridging capability or brokerage capacity of a node. Finally, closeness centrality is a measure of the closeness of a node to other nodes, and eigenvalue centrality measures the importance of a node in terms of its neighbors. For example, having a few popular co-authors or co-authors with many connections will provide you with a high eigenvector centrality, compared to having many unpopular co-authors or co-authors with fewer connections themselves. These measures were also investigated as a measure of social capital to increase research output in scientific collaboration networks [86], [87]. Table 3 provides the top ten authors within our dataset with respect to these centrality measures. Eigenvector centrality is not reported since all authors in our network have the same value for this measure.

D. PERFORMANCE ANALYSIS

Performance analysis involves quantitative evaluation of the scholarly contributions of various research constituents (authors, institutions, and countries) of a scholarly discipline [24].

The total number of cited references is 4,70,181 of which 65,230 are for unique journals, conferences, and pre-prints. The most number of references on a single paper is 530, and the least is 0. Along with Zipf law, for which we found partial support, we applied Bradford's law of scatter [51] on the cited references as well. According to this law, for a given scientific discipline "there are a few very productive periodicals, a larger number of more moderate producers, and a still larger number of constantly diminishing productivity" [88]. In other words, the cited references can be divided into three groups with decreasing productivity based on the number of citations received. The first group will have the least number of journals but as many citations as received by the next

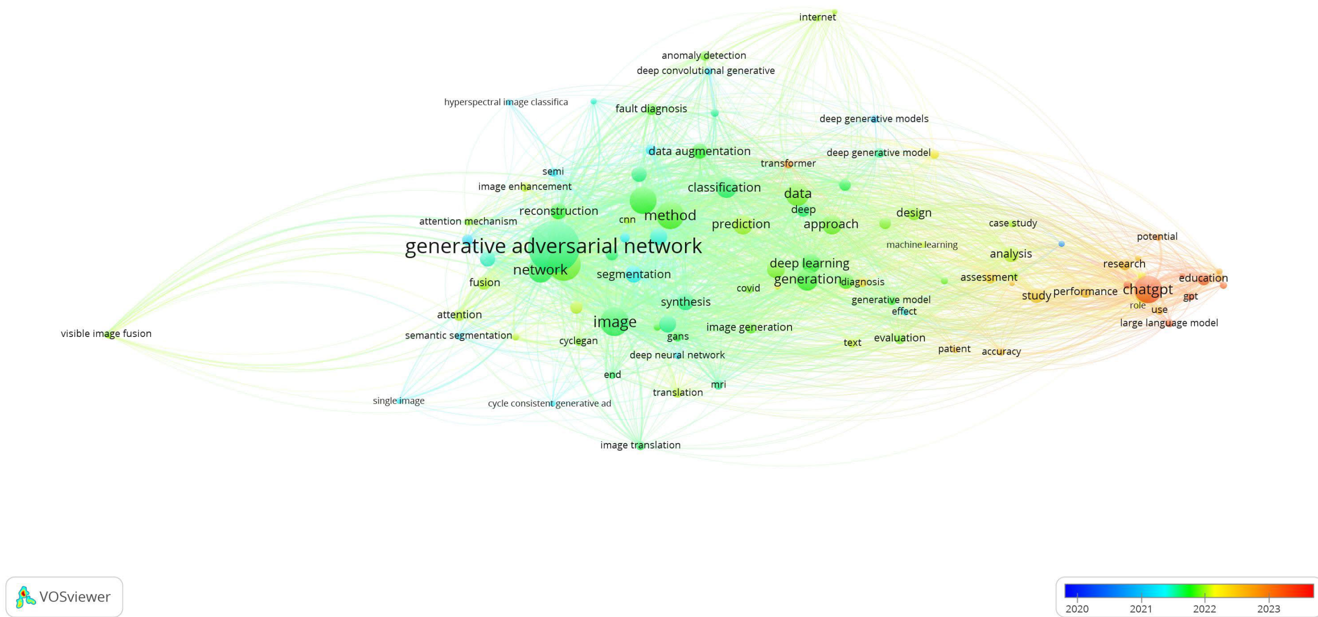


FIGURE 12. Co-word network visualization of prominent terms used in article titles over the years.

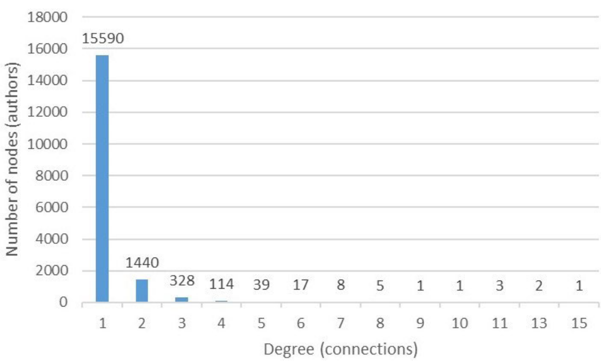


FIGURE 13. Degree distribution for nodes.

group, and the second group will have less number of journals than the third group (but with equal citation count). Further, the number of journals in each group will be proportional to 1:n:n^2 [89]. Since, the total number of cited references are 4,70,181, each group, as per Bradford's law will have approximately, 1,56,727 citations. Since, it is not possible to divide the cited references into three groups with this exact number, our three theoretical groups consist of 1,56,819 citations (group 1 with 44 journals), 1,56,606 citations (group 2 with 903 journals), and 1,56,756 citations (group 3 with 64,243 journals). Group 1 is often known as the nucleus of a discipline, and Bradford's law is sometimes used to determine the most influential or core journals in a discipline [90]. Ideally, the three groups must be in a geometric progression relationship of 1:n:n^2 (for the number of journals in each group), as stated above, which is unfortunately not the case here.

To fix the above issue, we applied the Leimkuhler model of Bradford's distribution [91], [92], which resulted in the three groups being closer to the theoretical Bradford's scattering. The new groups have 49 journals (with 1,61,938 citations) as core or nucleus, 1,767 within group 2 (with 1,81,193 citations), and group 3 with the remaining journals (and 1,27,050 citations). The resulting ratio of the third to the second group is 35.88795, while this ratio for the second to the first group is 36.06122, confirming that the three groups are now close to being in geometric progression, and hence loosely follow Bradford's law.

Table 4 lists the most prominent authors (number of articles > = 20) concerning the number of publications. There are 4,79,340 cited authors of which 14,687 are unique. Table 5 lists the most cited authors. The current institutional affiliations of these prominent authors are also reported. The ten most cited articles within our corpus and article titles are shown in Table 6 below. The purpose of including article titles is to reinforce the research topics further. The most cited articles also serve as a guide for future research directions. Based on Table 6, Generative Adversarial Networks and its optimization; and topics related to image processing; seem to be two encompassing research themes.

The top 10 journals publishing generative AI research and the most cited journals/conferences were already provided in Figure 7 and Figure 9, respectively. Concerning institutions, authors within our corpus are affiliated with 31,320 institutions, of which 3,836 are unique. There are 2,909 papers having authors with single institutional affiliations. Most papers have authors with two institutional affiliations (n = 55,46), followed by three (n = 52,74). The top institutions with the most author affiliations are shown in Figure 14.

TABLE 2. Prominent author keywords over the years.

Author Keyword	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Grand Total
Generative adversarial network					3	52	270	725	1141	1562	562	130	4445
Deep learning		1	1	1	3	24	112	229	375	542	217	53	1558
Training							8	83	174	231	53	12	561
Generators							12	85	146	201	40	4	488
Feature extraction					1		6	68	112	151	52	6	396
Machine learning					2	4	18	59	79	100	48	21	331
Artificial intelligence	1	1	2	2	6	9	18	34	40	65	65	61	304
Task analysis							5	42	90	113	24	3	277
Data augmentation						1	10	44	72	87	47	10	271
Convolutional neural network						6	23	35	47	69	33	3	216
Image reconstruction							6	33	57	84	29	5	214
Data models							2	22	46	98	35	5	208
ChatGPT											72	79	151
Anomaly detection							6	20	45	49	14	5	139
Neural networks						2	9	20	39	46	16	3	135
computational creativity	4	2	10	18	13	19	17	22	9	12	5		131
Conditional generative adversarial network							10	21	38	40	21	1	131
remote sensing						2	4	19	37	63	3	2	130
transfer learning						1	4	16	30	43	20	10	124
Attention mechanism							3	12	24	50	29	4	122
Fault diagnosis							6	11	32	53	11	6	119
Convolutional neural networks						2	14	11	26	45	18	2	118
Image segmentation						1	3	24	29	42	8	2	109
Super-resolution						3	6	22	24	36	11	7	109
Image fusion							1	14	34	35	20	3	107
Unsupervised learning						2	14	18	24	34	12	3	107
Semantics							2	17	36	43	6	1	105
Image synthesis						1	11	13	29	42	6	2	104

TABLE 3. Top 10 authors with highest centrality measures.

Degree centrality	Betweenness centrality	Closeness centrality
Lei, Yang (15)	Zhang, Hao (371)	Chen, Boyang (1)
Zhang, Ting (13)	Ma, Jiayi (293)	Korzynski, Pawel (1)
Li, Yang (13)	Zhang, Jing (247)	Doo, Florence X. (1)
Zhang, Yang (11)	Zhang, Hao (245)	Baek, Tae Hyun (1)
Zhang, Hao (11)	Batchuluun, Ganbayar (188)	Melnyk, Oleksiy (1)
Li, Wei (11)	Shi, Canghong (162)	Ebert, Christof (1)
Batchuluun, Ganbayar (10)	Le, Zhuliang (151)	Hmoud, Mohammad (1)
Zheng, Ziqiang (9)	Zhang, Xian (140)	Guo, Pengwei (1)
Li, Jie (8)	Yu, Keping (137)	Van Slyke, Craig (1)
Zhang, Jing (8)	Li, Yang (131)	Ellis, Amanda R. (1)

Except for Seoul National University in South Korea; most prominent institutions are located in the People's Republic of China except for a few in the United States.

20,620 funding agencies are sponsoring generative AI-related research projects based on articles within our corpus. Of these 17,849 are unique. These funding agencies are primarily from the People's Republic of China, and the United States. The European Union, Canada, and Germany have one prominent funding agency each. Interestingly, NVIDIA Corporation is the only major business organization funding generative AI research projects prominently. Apart from the other top keywords from Table 1, task analysis, deep generative models, and three-dimensional displays are keywords used by authors in research articles supported by grants from NVIDIA. Figure 15 shows the top funding agencies.

Finally, authors in our corpus belong to 123 countries, with the People's Republic of China at the top with 5,360 articles, followed by the United States of America with 1,974 articles, and South Korea in third place with 717 articles. Authors from England have authored 604 articles and 588 articles were written by authors from India. Figure 16 shows the overlay visualization network using VOSviewer software for the top 66 countries (minimum number of documents = 10) publishing generative AI research.

The size of the node represents the number of documents, and the node color is representative of the average publication year starting from mid-2020 till the end of 2022. The choice of this year's range is based on the most variation observable in the data. For instance, the number of articles published by authors affiliated with institutions within the United States of America is 1,974, and the average publishing year is 2021.72. The significance of this figure is that it not only shows

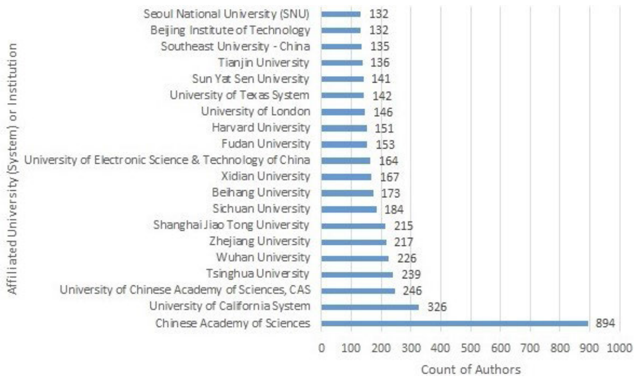


FIGURE 14. Prominent institutions.

TABLE 4. Prominent authors based on the number of articles published.

Author Name	Number of articles	Author Affiliation
Wang, Fei-Yue	37	Chinese Academy of Sciences
Li, Yang	33	Beijing Institute of Technology
Park, Kang Ryoung	33	Dongguk University
Zhang, Wei	28	Chinese Academy of Sciences
Liu, Yi	26	Tianjin University
Zhang, Hao	26	Wuhan University
Zhang, Yi	25	Sichuan University
Li, Jun	24	South China Normal University
Liu, Xin	24	Chinese Academy of Sciences
Li, Wei	23	Jiangnan University
Li, Jie	22	Xian Jiao Tong University
Yang, Xiaofeng	22	Emory University
Lei, Yang	21	Emory University
Li, Xin	21	University at Albany
Ma, Jiayi	21	Wuhan University
Wang, Lei	21	Wuhan University of Technology

TABLE 5. Most cited authors.

Author Name	Number of citations	Author Affiliation
Goodfellow I	5765	Google DeepMind
Isola P	2323	Massachusetts Institute of Technology
He KM	1742	Microsoft Research
Zhu JY	1548	Carnegie Mellon University
Wang Z	1455	University of Waterloo
Kingma D.P.	1438	Google Brain
Arjovsky M	1434	Google DeepMind
Ronneberger O	1301	University of Freiburg
Radford A.	1212	OpenAI
Ledig C	1123	University of Bamberg
Zhang H	1110	Google Brain

TABLE 6. Most cited articles.

Number of citations	Article Title
3248	"Generative Adversarial Network" [12]
1392	"Generative Adversarial Nets" [56]
1370	"Unpaired image-to-image translation using cycle-consistent adversarial networks" [93]
1364	"Adam: A method for stochastic optimization" [94]
1302	"Image-to-image translation with conditional adversarial networks" [95]
1195	"U-Net: Convolutional Networks for biomedical image segmentation" [96]
1161	"Wasserstein generative adversarial networks" [97]
1135	"Deep residual learning for image recognition" [98]
1114	"Photo-realistic single image super-resolution using generative adversarial network" [99]
1014	"Image quality assessment: from error visibility to structural similarity" [100]

the collaboration between authors affiliated with institutions located in these countries, but also depicts the emergence of countries such as India (average publishing year 2022.21), Saudi Arabia (average publishing year 2022.28), Thailand (average publishing year 2022.61) and Jordan (average publishing year 2022.97).

IV. DISCUSSION

Our findings show that there has been an increasing interest in generative AI, as evident from an increasing number of publications occurring in the past few years (especially after 2018). This growth is possible not only as a result of the availability of innovative and large datasets to train the models on, but also due to the growing interest from practitioners, commoners, and policymakers. Despite this increase in the number of publications, there seems to be a lack of articles summarizing the intellectual landscape of generative AI research using literature reviews, meta-analysis, and bibliometrics. There is a decent amount of review and bibliometrics research on artificial intelligence [101], [102], [103], and its application to various industries [104], [105], [106] but the lack of such research specific to generative AI is rather surprising. Hence, our study aims to fill this gap by conducting bibliometric analysis of 10 years of generative AI scholarly research.

The bibliometric analysis of the research articles published in the field of generative AI over the past decade shows important research themes and recent trends. These results are based on the techniques of citation analysis (article co-citation and journal co-citation), and consider the most cited articles for deriving the thematic areas. Since the citations received by the articles can change over time, the underlying knowledge areas may also change (although not soon). This is one of the limitations of the current study. Based on the technique of co-citation analysis of articles we found technological developments (such as research on generative adversarial networks), and application-oriented research (for example, research on image processing and image quality) as two broad overarching themes addressed by researchers.

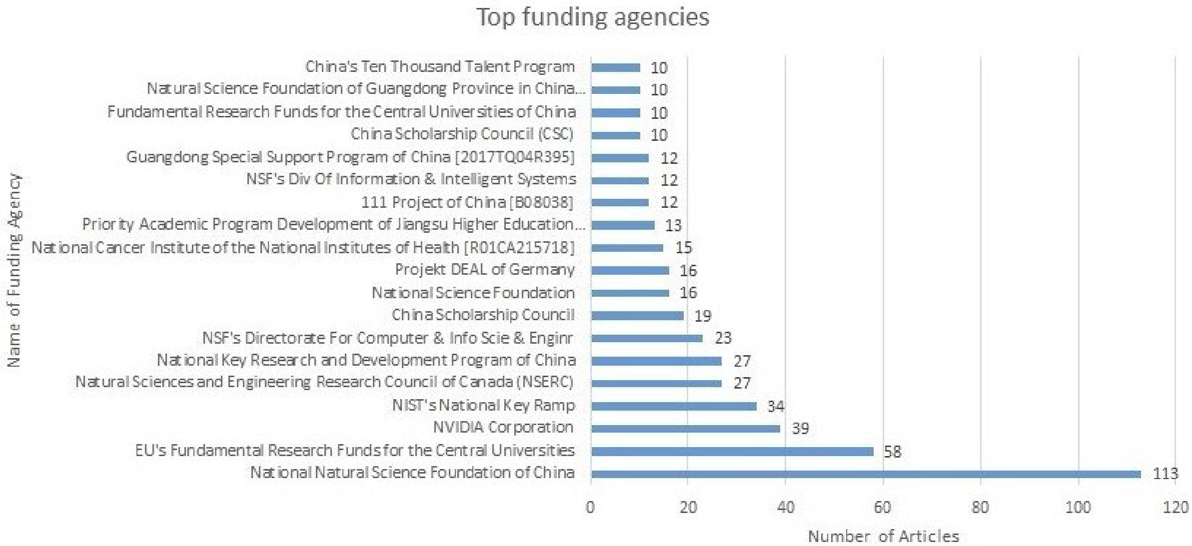


FIGURE 15. Top funding agencies.

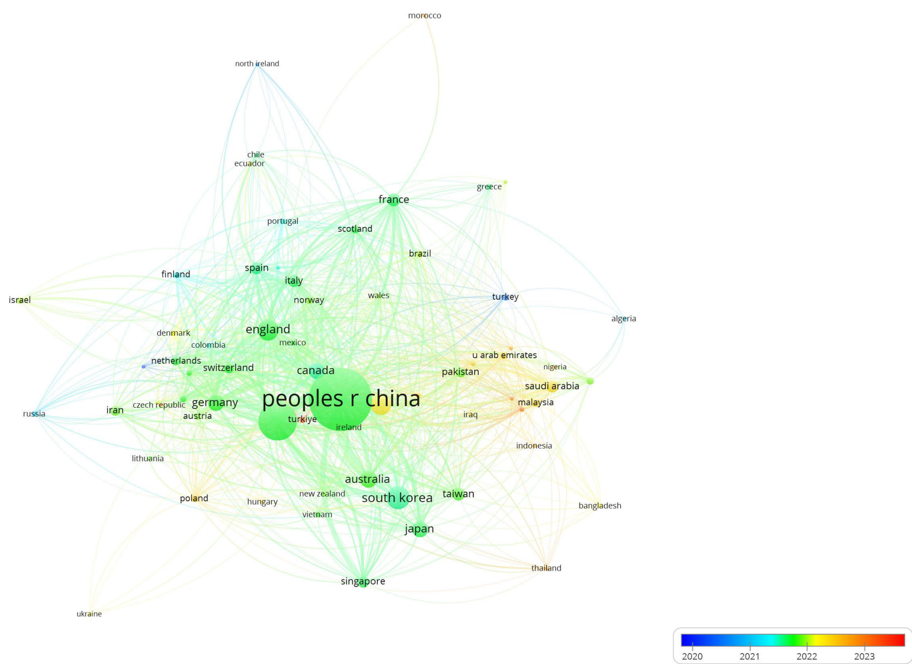


FIGURE 16. Overlay visualization of collaboration network for countries.

Along with article co-citation, journal co-citation is also used to delve deeper into the underlying research themes. Like the findings from article co-citation analysis, two overarching themes emerged – technological advances with research concentrating on pattern recognition, artificial intelligence, computer vision, neural information processing and machine learning, and application-oriented research such as geosciences, remote sensing, health informatics, and clinical medicine [107], [108]. To further investigate these research themes, text mining with frequency counts of the most prominent terms used in the article titles, and by authors (as author keywords), are analyzed. Generative adversarial networks, adversarial networks, deep learning, deep generative models, machine learning, artificial intelligence, convolutional neural networks, and simulation, were found to be terms prominently representing the technical advancements. On the other hand, fault diagnosis, feature extraction, anomaly detection, remote sensing, computational creativity, and data models, were specific to terms representing applications of generative AI. Terms based on image processing research such as synthesis, segmentation, translation, reconstruction, enhancement, and super-resolution were also prominent. ChatGPT is a frequent term gaining widespread attention recently.

Although co-citation analysis on articles and journals along with text analysis on frequent terms shows the presence of certain research themes, these techniques do not show the gradual evolution of these themes over time. Hence, frequency counts of author keywords over the years and overlay visualization of the co-word network based on the terms used in the article titles are used to show such gradual developments. Few keywords such as GAN, deep learning, training, feature extraction, and generators, were found to be used more frequently in recent years (after 2019), while others such as AI, and computational creativity were used across the article corpus. Recent years also saw the emergence of the application of generative AI research in healthcare, and education and the application of large language models in the form of ChatGPT, as evident from the term co-occurrence visualization network.

In terms of prominent journals, IEEE Access is the journal publishing the most articles, followed by the journal Sensors, and Applied Sciences. On the other hand, the IEEE conference on computer vision and pattern recognition, followed by the preprint articles, and Lecture Notes on Computer Science, were the most cited knowledge sources. This finding corroborates the general perception of the importance of conferences and timely publications in the academic discipline of computer science [109].

Social network analysis and performance analysis were carried out to show the important constituents contributing to research on generative AI from the past decade. Authors and institutions from the People's Republic of China were found to be important contributors. Given the technical and contemporary/cutting-edge nature of generative AI research, researchers from academia and industry (such as OpenAI, Google DeepMind, and Microsoft) were found to be actively publishing, with NVIDIA Corp being one of the important funding agencies. Finally, co-authorship network for countries shows the emergence of authors affiliated with certain nations, such as India, Jordan, and Saudi Arabia, to be published recently.

A. APPLICATION OF GENERATIVE AI WITHIN OTHER DISCIPLINES

Apart from the application of generative AI techniques and algorithms such as Generative Adversarial Networks, deep learning, and convolutional neural networks to image processing and computer vision, applications to other disciplines are evident from the article corpus, as briefly discussed below.

1) HEALTHCARE AND HEALTH INFORMATICS

Generative AI is revolutionizing healthcare by helping develop tools that not only improve patient care but also help medical research. Virtual health assistants are one such example. These are programs aimed at providing personalized patient care with functionalities such as conversing with patients, providing them with health advice, reminding them to take their medications, and providing mental health assistance. Although research involving the diagnosis of patient disease based on medical/lab reports, and images (for instance, CT and MRI), using clinical decision support systems, had been well-established, generative AI offers new potential and opportunities [110], [111]. This makes the process of diagnosing diseases faster and more accurate, which is really good for patients [112], [113], [114], [115].

In medical research, generative AI is expediting the process of novel drug discovery. The models based on generative AI can predict the behavior of molecules and assist in simulating experiments, allowing for quicker and less expensive discovery of medical treatments. In short, by using generative AI, healthcare is becoming more efficient, precise, and tailored to each person, opening up new possibilities for how well we can be taken care of and how quickly we can find new treatments [116], [117].

2) EDUCATION

Large Language Models (LLMs) are natural language processing and generative AI models that work with human language and are capable of understanding as well as producing human language texts [118]. ChatGPT, developed by OpenAI, is a powerful AI-based chatbot, based on the large language model [119]. Capable of conversing in natural language, ChatGPT has gained widespread attention, not only from society but also from academia. This is also evident from numerous recent research publications aimed at understanding the repercussions of using ChatGPT by the faculty, researchers, and students in an academic setting.

Some of this existing research views ChatGPT more favorably with an aim towards exploring the potential benefits in a university setting such as personalized tutoring, automated grading, and interactive learning [120]. Usefulness of ChatGPT in academic writing and optimization, enhancing the critical thinking of students, and enhancing the learning experience of students are other opportunities in this domain [13]. Despite these potential benefits and opportunities, others have investigated the drawbacks and challenges of using ChatGPT in an academic setting. Disruption of educational policies and ethical guidelines toward students' use of ChatGPT and potential negative effects on academic publishing are prominent examples [13], [121]. Others have explored ChatGPT's application to specific disciplines such as medical education [25], science education [122], environmental education [123], and management education [124]. Regardless of the potential benefits, opportunities, issues, and challenges, generative AI LLM applications such as ChatGPT are here to stay for the foreseeable future and will disrupt Universities and research institutions.

3) GEOSCIENCE AND REMOTE SENSING

Generative AI tools and techniques for image processing, image synthesis, and knowledge discovery from data have found applications in earth science, remote sensing, and climate science [125], [126], [127], [128]. Image classification, object detection, image denoising, image generation, description generation for images, and processing of seismic data are a few applications.

4) INTERNET OF THINGS (IoT)

Including generative AI in intelligent IoT applications in many industries is pushing the boundaries of creativity. Generative AI enables IoT devices to understand and interact with their surroundings in a more human-like manner, enhancing their ability to perform complex tasks with greater efficiency and precision. This advancement is not just about automating routine tasks; it's about creating intelligent machines and systems that can learn from their environment and make decisions in real time. This will open up new opportunities for manufacturing and service industries. For example, in the case of autonomous vehicles, generative AI plays a crucial role in processing vast amounts of sensor data to make split-second decisions about navigation and safety. By simulating countless driving scenarios and imitating driver behavior, generative AI techniques help vehicles learn to respond to a variety of road conditions and obstacles, making self-driving cars safer and more reliable [129], [130], [131], [132].

Furthermore, in mobile networks, generative AI contributes to optimizing data flow and managing network traffic, ensuring seamless connectivity and improved user experiences [133], [134]. Predicting network loads and identifying potential disruptions allows for proactive management of network resources, enhancing the efficiency and reliability of communication systems.

5) CYBERSECURITY

Similar to education, existing research on applications of generative AI within the cybersecurity discipline is mixed and includes both opportunities as well as challenges. For instance, ChatGPT has been discussed as a potential cybersecurity threat in a few studies. Generative AI's use for developing cyber attacks such as social engineering attacks, phishing attacks, and malware creation are a few negative aspects highlighted in the literature, with calls for organizations to train employees to detect such smart attacks [135], [136]. On a positive note, generative AI is also viewed as a game-changer by others, employing sophisticated algorithms for designing security systems aimed at detecting and counteracting cyber threats in real-time. Deep learning models can analyze patterns in data to identify anomalies that could signify a cyber attack, enabling faster and more effective responses to emerging security challenges [137].

V. CONCLUSION

This study presents a bibliometric analysis of generative AI research published in the last decade (2013-2024). The techniques of co-citation analysis (on articles and journals) and frequency counts on author keywords and title terms are used to identify the prominent research themes (research question 1). Natural language processing techniques involving frequency counts of author keywords over the years and co-word network analysis on terms from the article's titles are used to investigate the progression in research themes (research question 2). Finally, the co-authorship network's performance and social network analysis identify prominent research constituents (research question 3). Based on the findings from this study, we conclude that generative AI research in the past ten years has been highly technical, with most research focusing on developing deep neural networks and related techniques and their application to image processing, pattern recognition, and computer vision. Hence, we found slightly distinctive but overlapping research themes.

The research presented in the current study makes several useful contributions to the existing body of knowledge of generative AI academic research and has useful implications for the practitioners working in this domain. First, our study allows researchers looking forward to publishing in this area to understand the existing landscape and the current state of generative AI scholarly research. Second, it allows us to understand the evolutionary nuances and emerging trends. Based on the scholarly publications in recent years, we know that generative AI research is moving from the technological towards human and organizational aspects. Hence, as a third contribution, our study allows (to some extent) researchers to recognize knowledge gaps lying at the intersection of generative AI and other disciplines (such as marketing, human resources, etc.). The same is true for practitioners and developers, who must strive to work on unique problem scenarios involving applications of generative AI in an organizational setting (for instance, generative AI assisting with business processes, knowledge management, or interacting with clients/customers as chatbots [138]). Finally, with performance analysis, our study objectively assessed research contributors and their scholarly impact. It allowed us to find that certain authors, institutions, businesses, universities, and countries, are more prominently involved than others in carrying out and supporting research in this area.

Although our study provides a good understanding of the existing scholarly landscape of generative AI research and its evolution over the past decade, the research presented is not without limitations and possible future directions. One major drawback of bibliometric studies, such as ours, is that they do not consider the context of citation [65], [139]. For example, an article may cite another article for several reasons that will go unaccounted for during bibliometric analysis. In other words, every citation count is treated equally. Hence, other techniques such as text analysis, social network analysis, and co-word analysis must complement the results from bibliometrics (as used in this study). We must also be cautious when making assertions about future research directions and possible applications, especially for a dynamic field such as generative AI, only based on the existing scholarly structure.

Although no one knows what lies ahead for generative AI, one can be sure that in the long run, the focus of academic research as well as industrial applications will progress from technical AI towards human and organizational aspects, especially during and after the widespread adoption of generative AI applications. This is also evident from recent publications focused on the implications of ChatGPT adoption in different industries and application scenarios [28], [140], [141]. Thus, we believe that generative AI academic research will eventually move away from its existing technical aspects towards interdisciplinary aspects. At that time, identifying reference disciplines or knowledge sources, theories, models, and frameworks from different scholarly fields will be a promising research question as an extension of the current study. Although this will open new research opportunities, especially for computational social scientists, it will also create many issues and challenges for policymakers, governments, and business organizations. In the wake of such advancements, it is notable that the United States Government's current administration had recently issued "an executive order on safe, secure, and trustworthy AI" [142]. A similar law was proposed by the European Union in 2021 and later approved in March 2024 [143]. Historically, technological developments have driven organizational, societal, and legal changes, and a similar trend is evident with generative AI. We must prepare ourselves and embrace what lies ahead once generative AI applications see widespread adoption and usage by individuals, businesses, and government organizations.

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