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Literature Review

A Bibliometric Review of Analyzing the Intellectual Structure of the Knowledge Based on AI Chatbot Application from 2005–2022

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ABSTRACT

This research approaches the problem of artificial intelligence chatbot applications from a new perspective. With the development of innovation, many firms are using artificial intelligence chatbots to manage their business and build relationships with their customers. Thus, this study aims to offer bibliometric assessments of the expanding literature about AI chatbot services. We used the VOS Viewer software to analyze the data based on Scopus from 2005 to 2022. We extracted and examined the data from several AI chatbot service bibliometric reviews. Given the data, we form 571 peer-reviewed papers from the journal. After analyzing the data, the researchers found the most influential work, authors, and co-cited authors on AI chatbots. Similarly, the researchers, based on the author's co-citation analysis and the intellectual structure, distinguish between "computer science", "chatbot service", and "digital health". Computer science is the most critical discipline regarding AI applications.

Keywords: AI Chatbot, Bibliometric Review, Intellectual Map, VOS Viewer.

INTRODUCTION

Many economic sectors have benefited from Artificial Intelligence (AI) innovations, often known as machine intelligence (Kietzmann & Pitt, 2020). Increasingly, companies use Artificial Intelligence (AI) to alter their brands to decrease costs, boost efficiency, raise revenue, and enhance the customer experience (Adam, Wessel, & Benlian, 2021). Experts predict that by 2030, artificial intelligence might add $15.7 trillion to the global economy (Adam et al., 2021). From $1.3 billion in 2010 to $40. 4 billion in 2018, with over 3000 enterprises receiving over $400,000 in funding, significant investments in AI startups have increased dramatically worldwide. Investing in artificial intelligence is predicted to increase by as much as three times by 2024 (Kietzmann & Pitt, 2020).

During the COVID-19 epidemic, when people were confined to their homes and human agents were few, AI chatbots overgrew. Consumers today rely heavily on digital resources like AI chatbots to research items, decide which ones to buy, and ultimately choose which brands to buy (Adam et al., 2021). By 2026, the chatbot industry is predicted to be worth $10.5 billion. From 2019 to 2026, the customer service sector of the AI chatbot market is expected to expand by 31.6% (Adam et al., 2021). The bibliometric review approach, which aims to collect and evaluate all relevant literature on a topic, has not been used in previous reviews (Zupic & Čater, 2015). This bibliographic study aims to compile data about artificial intelligence chatbot services and analyze the conceptual theories. The study aims to accomplish the following questions through its research:

1. How many AI chatbot services are there, how quickly are they growing, and where are they most prevalent?

2. Which journal has contributed the most citations based on the AI chatbot?

3. Which cited and co-cited authors have contributed most to the literature on AI chatbot applications?

4. What is the "intellectual framework" of the AI chatbot service literature?

This research used an extensive bibliometric analysis of the literature on artificial intelligence chatbots. The analytical method examined bibliographic data from 571 chatbot service evaluation publications. This study employed quantitative bibliometric methods, including productivity, citation, co-citation, and scientific mapping (Zupic & Čater, 2015; Van Eck & Waltman, 2018). As was said earlier, this topic is new in studying AI conversational services. This analysis examined more 2005-2022 documents. So, this study will examine the growing volume of AI chatbot service knowledge using bibliometrics.

LITERATURE REVIEW

Definition of Chatbot

Chatbots are computer programs that mimic human communication by using Artificial Intelligence (AI) and Natural Language Processing (NLP) to comprehend requests from customers and provide automated replies (Adamopoulou & Moussiades, 2022a). Without human involvement, chatbots may help consumers quickly locate the answers to their inquiries using text or audio input (Shawar & Atwell, 2007). These days, customers can find chatbot technology in various settings, from smart home speakers to enterprise messaging platforms. The newest generation of AI chatbots is frequently referred to as "virtual agents" or "virtual assistants" (Chaves & Gerosa, 2021). Siri, Google Now, and Amazon Alexa take voice commands, and customers can even text them. For example, Zhou, Gao, Li, and Shum (2020) found that customers may ask the chatbot conversational questions about their needs, and it will respond with information and further questions to narrow their search. Formerly, chatbots were text-based and could only respond to a small range of predefined questions with replies created by the chatbot's creators. Similar to an interactive FAQ (frequently asked questions), they were adequate only for the queries and answers with which they had been programmed, and they proved incapable of handling anything more sophisticated or unexpected (Ranoliya, Raghuwanshi, & Singh, 2017).

Chatbots have evolved over time to incorporate additional rules and natural language processing, allowing for a more conversational experience for the end user (Ghose & Barua, 2013). To be more precise, modern chatbots understand their surroundings and improve their language skills as they interact with more and more people. Modern AI chatbots employ NLU (natural language understanding) to comprehend the user's wants (Ait-Mlouk & Jiang, 2020). The next step is to employ cutting-edge AI capabilities to determine what the user is attempting to do. These systems depend on machine learning and Deep Learning (DL), both forms of AI with their subtleties, to build a database of questions and answers based on user interactions that become more specific over time (Braun, Mendez, Matthes, & Langen, 2017). This enhances their capacity to anticipate and meet the requirements of their users.

Furthermore, some modern chatbots employ sophisticated algorithms to deliver exceptional replies. Consumers are using AI chatbots for anything from interacting with smartphone apps to operating specialized products like intelligent thermostats and kitchen appliances (Xu, Liu, Guo, Sinha, & Akkiraju, 2017). The uses in the corporate world are as diverse. Marketers use artificial intelligence chatbots to tailor client experiences (Bariş, 2020), IT departments to facilitate computer science to stimulate human conversation (Um, Kim, & Chung, 2020), and customer healthcare service departments to expedite incoming messages and point customers in the right direction (Oh, Lee, Ko, & Choi, 2017).

History of Chatbot

Although chatbots have been for some time, it is only in the past few years that they have seen widespread adoption by both consumers and enterprises. ELIZA was the first chatbot (Weizenbaum, 1966), and other well-known chatbots were created in the latter part of the twentieth century (Adamopoulou & Moussiades, 2020b). For example, the WeChat bot creates a social network and facilitates the development of elementary-level conversational programs. It has become a model for how businesses and marketers may save costs without sacrificing the quality of online customer interactions. Although WeChat is less powerful and has several drawbacks compared to popular messaging platforms like Facebook Messenger, Slack, and Telegram today, customers can still build a brilliant bot on the platform (Zumstein & Hundertmark, 2017).

The first wave of artificial data technologies used to create chatbots debuted early in 2016. With the help of Facebook and other social media platforms, programmers may create a chatbot for a company's brand or service, allowing users to do various tasks within the messaging app (Kull, Romero, & Monahan, 2021). Now that chatbots are becoming commonplace, users live in the conversational interface era.

Economics of Chatbot

AI chatbots' deep learning capabilities make interactions more precise over time, weaving together a web of appropriately worded replies as they engage with people. An AI chatbot's replies improve the longer it has been in use. As a result, an AI chatbot trained using deep learning may be better able to respond to a question, and the underlying purpose of the question than one trained with more recently merged algorithm-based knowledge (Smutny & Schreiberova, 2020). With algorithm-based knowledge, chatbots create value for organizations and customers using modern AI chatbots (T. T. Nguyen, Le, Hoang, & T. Nguyen, 2021).

Before the advent of fully developed e-commerce, customers who wanted answers to their inquiries, concerns, or complaints had to send an email or give the company a call. Nonetheless, it is a continual and expensive effort for many companies to staff customer service departments to meet unforeseen demands and retrain workers to respond consistently to identical or recurrent requests at all hours of the day or night. Chatbots may now manage consumer contacts 24/7, all while reducing expenses and increasing response quality (Smutny & Schreiberova, 2020). By taking over mundane chores, chatbots streamline processes and increase productivity. With its instant availability to an unlimited number of users simultaneously, a chatbot may also do away with the need for customers to wait for customer service over the phone or through other channels like email, chat, or the web. Customers are more likely to be loyal to a brand if they had a positive experience (Trivedi, 2019).

The cost of maintaining a 24-hour customer service center is high. It may also be impossible for other divisions, such as human resources. Outsourcing this task has spawned a whole industry but comes at a high price. Also, it lessens a company's ability to direct how its brand communicates with its target audience. Nevertheless, a chatbot is available anytime and assists the firms in defense during peak times (Lasek & Jessa, 2013). Using a chatbot can at least lessen the number of customers who need to speak with an actual person, which can save money by keeping firms from hiring more people to deal with the growing demand.

Lead generation and conversion rates in sales may benefit from using chatbots (Meyer-Waarden et al., 2020). For instance, a consumer looking through a website for a product or service can have inquiries about the various available options and how they work. A chatbot can answer these questions and guide the customers toward a more informed buying decision (Khoa, 2021). Moreover, the chatbot may qualify the lead before connecting the buyer with a qualified sales representative for more sophisticated purchases through a multistep sales funnel. Choosing a chatbot platform may be simple, and the benefits to businesses and customers can be substantial. Companies may save money while still satisfying customers' need for instantaneous service using a conversational channel (Abdulquadri, Mogaji, Kieu, & Nguyen, 2021).

An online store might use a chatbot to tell customers more about what they are looking at, differentiate between similar models, and supply supplementary resources like how-to videos and user guides (Nichifor, Trifan, & Nechifor, 2021). Similarly, an enterprise company's human resources department may approach a developer needing a chatbot to provide employees with round-the-clock, self-service access to benefit information and ease of navigation.

METHODOLOGY

This section introduces bibliometric analysis performed to analyze related papers with AI chatbot service. The identified process of the source is from the scientific database of Scopus.

Identification of the Source

Many authors study the review and prefer to lay it out in the PRISMA (Preferred Reporting Items for Systematic Reviews and Analyses) (**Figure 1**). PRISMA can provide details such as search terms and exclusion criteria in the screening procedures (Moher, Liberati, Tetzlaff, & Altman, 2009).

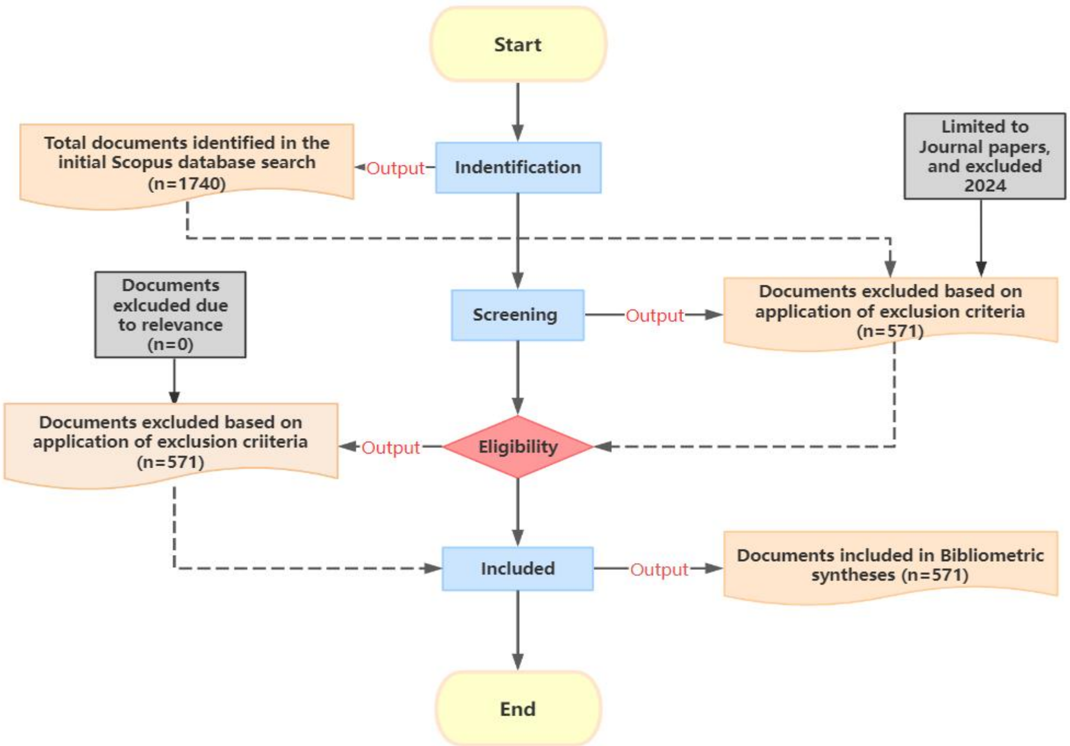

Figure 1. Identification of Sources with Prisma Flowchart

Scopus is a digital database widely used for bibliometric assessments (Zupic & Čater, 2015). That is because Scopus can cover many areas (Griffith, Small, Stonehill, & Dey, 1974). This study focuses on artificial intelligence chatbot reviews, which rely on its database. With the chatbot services in locating historical sources, this advantage makes it a fantastic resource for interdisciplinary social science research (Falagas, Pitsouni, Malietzis, & Pappas, 2008; Mongeon & Paul-Hus, 2016).

First, several variations of AI and AI-related search terms (e.g., AI OR artificial intelligence) were utilized to find reviews of the chatbot service (e.g., consumer chatbot service OR customer chatbot service). This search technique is effective since it retrieved papers from academics actively developing and publishing AI chatbot services (Garfield, 2004). However, this search approach may also be limited but can be relevant to "artificial intelligence" (e.g., medical in AI, AI in computer science, chatbot service) (Van Eck & Waltman, 2010). Besides, it is essential to remember that the keyword searches used for the preliminary review included not just author-defined keywords but also text from titles and abstracts of publications indexed by Scopus (Krening & Feigh, 2018). So, there were numerous opportunities to locate "AI chatbot service" perspective articles in the literature on artificial intelligence.

Second, documents used Scopus filters and were manually inspected based on predetermined criteria for rejection (Zupic & Čater, 2015). In this way, researchers constructed a "Scopus list" of relevant papers about AIC chatbot services (Van Eck, Waltman, Dekker, & Van den Berg, 2010). Bibliographic information associated with the Scopus list was downloaded as an Excel spreadsheet (Hummonb & Doreian, 1989). That is why all the best evaluations on AI for chatbots have assembled their datasets, which researchers can find in Scopus.

Last, the researchers have created a single Excel document including all AIC review databases. There were 571 rows of bibliographic information from Scopus in the main spreadsheet (columns). Data includes author names, document titles, authors' affiliations, abstracts, funding information, citation data, and co-citation data (Liang, Lee, & Workman, 2020). As was previously noted, the "findings" were discussed in numerous studies published by the AIC. The reviews were subjected to bibliometric analysis, which included citation and co-citation analyses (Garfield, Pudovkin, & Istomin, 2003).

Data Analysis

The bibliographic data needed to be examined and rectified for "consistency" in the expression of author names before any data analysis could begin (Van Eck & Waltman, 2010). One example is Weston Jones, whose name appears both as "Weston, J." and "Weston, J. L." in several sources. A "thesaurus file" was made to handle the "disambiguation" of author names. During data analysis, the thesaurus file directs VOSviewer analytical software to substitute a generic term for each possible variation of a given name (Van Eck & Waltman, 2010). Finding solutions to the research questions that steered this evaluation necessitated an analysis of authorship trends (Small, 1997). The entire database was used in all analyses (i.e., the master spreadsheet).

With the help of VOSviewer 1.6.8, science mapping, we could see connections between papers on AI chatbot services written by different authors (Zupic & Čater, 2015). It has been shown that the "productivity analysis" aimed to identify the most related AIC researchers. The full dataset was analyzed in this study using VOSviewer and Excel (Van Eck & Waltman, 2011). VOSviewer's "citation analysis" was used to determine how often each author of the 571 papers comprising the review database was cited in other Scopus articles (Small & Griffith, 1974). In this research, this indicator is known as the number of "Scopus citations."

This is because there are variations in the depth of the documentation. Scopus is more often used in data analysis than Web of Science in citation output while less than Google Scholar (Merton, 1973). In this study, the researchers study three aspects: productivity analysis, co-citation, and intellectual framework. This is because high-impact authors, journals, and publications are believed to significantly affect the development of research and study fields (Price, 1965). Therefore, the Scopus citation analysis was augmented by a co-citation analysis performed in VOSviewer 1.6.8. (Zupic & Čater, 2015).

In order to maintain a comprehensive record of author relationships, the VOSviewer program additionally keeps track of the "citing authors" (Small, 1973). By looking at the "authors cited in the review database," co-citation analysis can pinpoint relevant authors. Researchers often utilize co-citation analysis to find "connections" between prominent researchers in the same field (Small, 1997). For example, if a co-citation study shows that Weizenbaum and Atwell are "often co-cited" (e.g., 25 times), we can infer that their works are conceptually compatible (Zupic & Čater, 2015; Price, 1965; White & McCain, 1998).

Using co-citation matrices derived from cited authors, VOSviewer performs author co-citation analysis (ACA), producing a "science map" of the literature (Price, 1965). This analysis of AI chatbot services utilized an ACA map to demonstrate author overlap graphically (Skupin, Biberstine, & Börner, 2013). When taken as a whole, these findings illuminated the scholarly traditions or "intellectual framework" underlying the literature (Zupic & Čater, 2015; Price, 1965).

RESULTS

In this section, the researchers discuss and answer the four research questions. Production growth and distribution have been analyzed to answer the first research question. Then, the researchers found the most cited journal based on Scopus. Moreover, cited and co-cited authors are discussed to answer the third question. Last, the researchers also develop an intellectual framework to explain the AI chatbot service literature.

Analytical Characterization

Adam et al. (2021) forecasts that the artificial intelligence chatbot will progress significantly in the following years. Indeed, many articles have appeared in print during the previous few years. **Figure 2** presents the total number of documents that have grown dramatically in distribution from 2005 to 2022. Primarily, the papers in 2022 have been published almost two times compared with 2021.

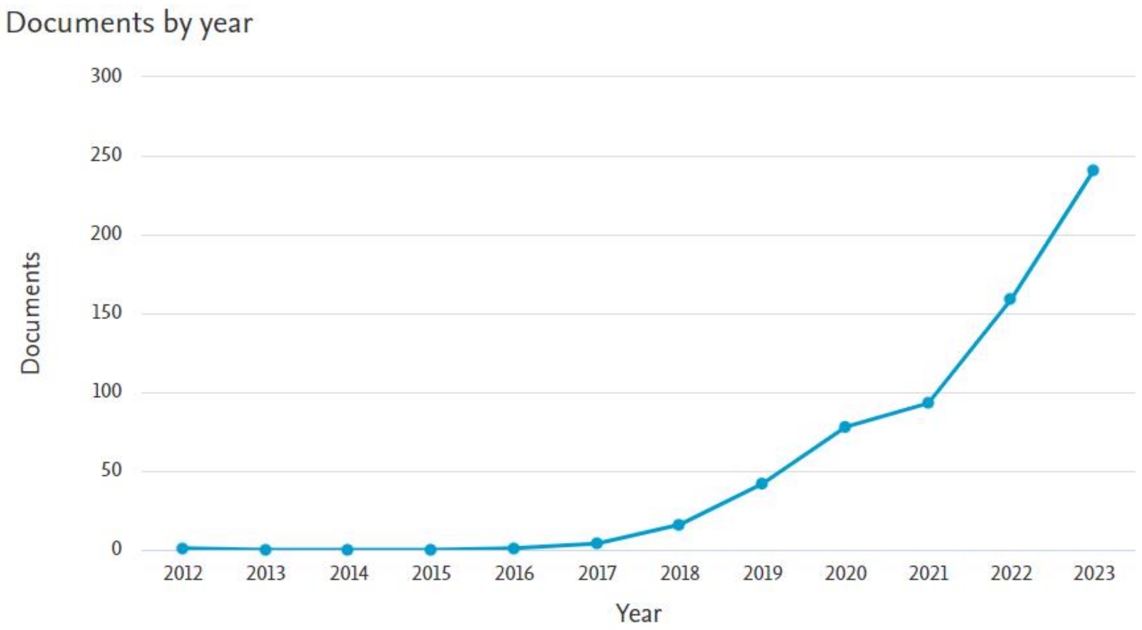

Figure 2. The Increasing Documents of AI Chatbots, 2005 to 2022 (n=571)

Besides, AI chatbot is a new trend topic in recent years, and knowing the subject domains is worthwhile. The bibliometric review can provide clear and detailed information for disciplinary knowledge, so the researchers extract the data model from Scopus. **Figure 3** introduces the most important study of documents by subject area. Notably, computer science, engineering, social sciences and business, management, and accounting researchers have taken up 61.7% of the total literature. This hints at opportunities for substantial new developments to emerge from theoretical viewpoints and approaches from other fields.

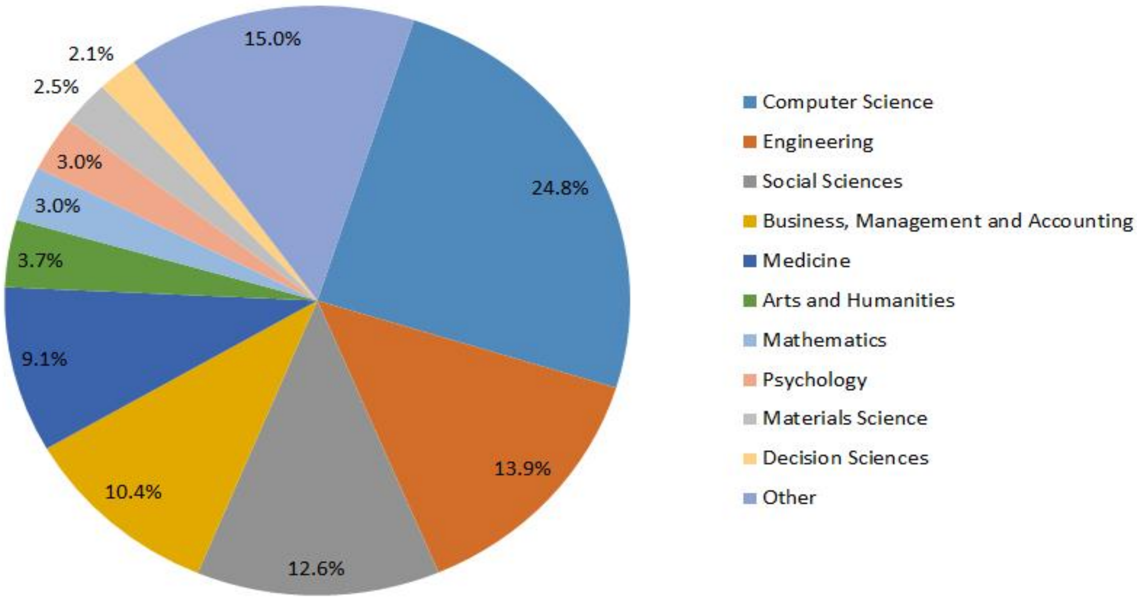

Figure 3. The Most Important Study of Documents by Subject Area, 2005 to 2022 (n=571) (Note: The subjects are less than 2% combined in another group.)

Figure 4 is a world map illustrating AI chatbot literature's worldwide influence and concentration. The result is based on its roots in a particular country or area. The United States has the most published papers worldwide, which takes up 119. Then, India, South Korea, the United Kingdom, and China follow closely. Broadly, North America and Asia have contributed the most papers. Indeed, the papers from North America and Asia has been taken up more than 60 percent based on the database from Scopus.

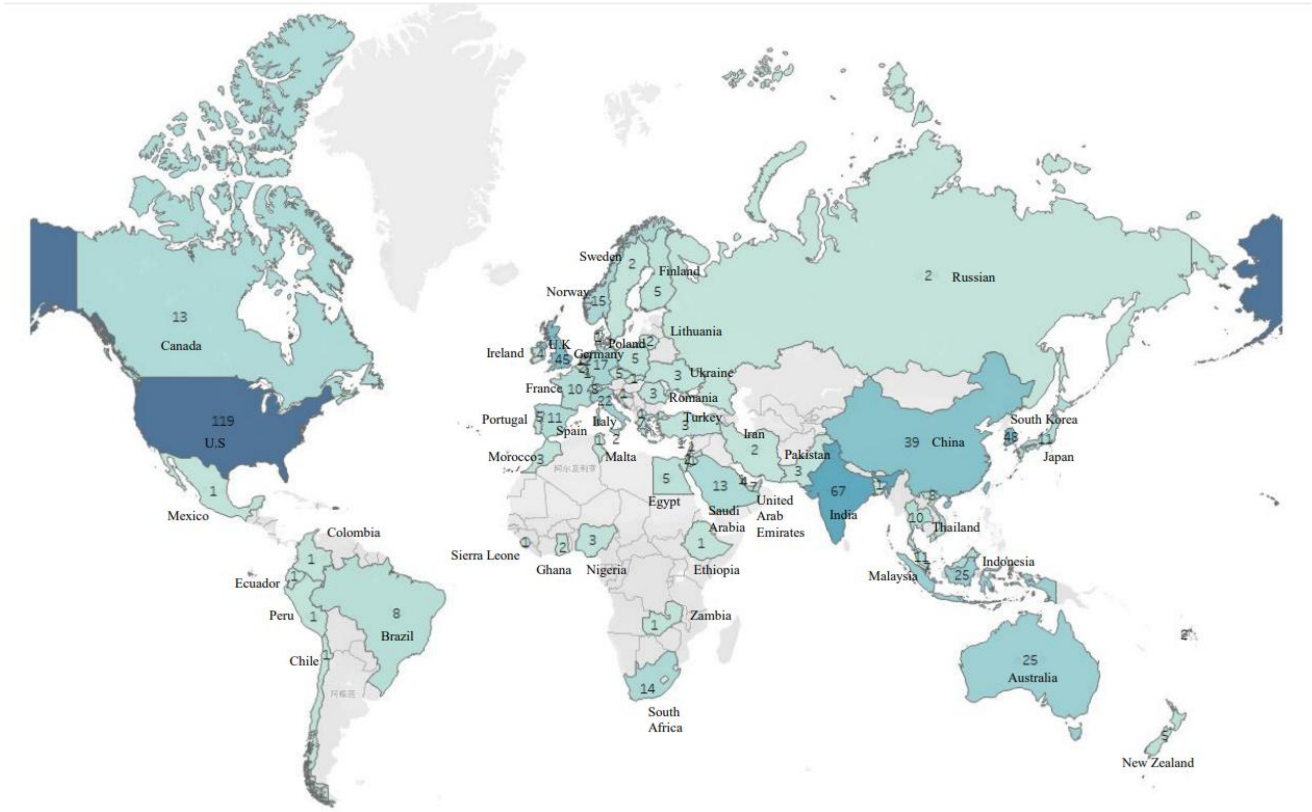

Figure 4. Geographical Distribution of Chatbot Service Papers across the World

Citation Analysis of Journal Impact

Trapp (2020) mentioned that journal impact from Scopus can help researchers quickly find a suitable journal. Indeed, the database of Scopus can provide a reliable source for scholars to consider when they need to find a suitable journal to publish (**Table 1**). The most top cited journal on AI chatbots is Computer in Human Behavior. The other highly cited journals are Journal of Business Research, Digital Health, and Electronic Markets. The academic publication Computers in Human Behavior takes a psychological approach to study how people interact with computers. The AI chatbot is one of the suitable topics to discuss human-robot interaction. That's the reason that many researchers submitted their papers in Computers in Human Behavior. Besides, with the economic development, many firms use the chatbot as their representative to connect with their customers. Business studying in AI chatbot has increased a lot in recent years. Journal of Business Research has been ranked in second place. It is a proper journal to publish the relationship between the customers and companies. Moreover, Journal of Business Research investigates a broad spectrum of decision-making environments, processes, and activities to provide insights with application in theory, practice, and society. Furthermore, hospitals have also built their digital platform to help patients. Digital Health, as one of the most influential journals, is suitable for a scholar who wants to publish advanced technology in the health industry, such as an AI chatbot application. Here are the most influential ranking journals.

Table 1. The Top Cited Journal of an AI Chatbot, 2005 to 2022

Rank	Source	Documents	Citation
1	*Computers in Human Behavior*	10	801
2	*Journal of Business Research*	10	405
3	*Digital Health*	4	170
4	*Electronic Markets*	4	168
5	*IEEE Access*	8	132
6	*Journal of Medical Internet Research*	12	127
7	*International Journal of Bank Marketing*	4	119

Rank	Source	Documents	Citation
8	*Journal of Retailing and Consumer Services*	4	102
9	*Sustainability* (switzerland)	5	95
10	*Journal of Service Management*	5	91
11	*Applied Sciences* (switzerland)	15	47
12	*Information Systems Frontiers*	6	44
13	*Electronic Commerce Research and Applications*	4	33
14	*Proceedings of the ACM on Human-computer Interaction*	4	32
15	*Telkomnika (Telecommunication Computing Electronics and Control)*	4	30

Scopus Citation and Co-citation Analysis of Author Impact

Citation Analysis of the Author

To answer research question 3, the researchers have analyzed the author's citation and co-citation, respectively. Small (1997) claims that bibliometric research can reveal which academics have contributed significantly to the body of knowledge. Scholars may be identified by their fields of study, countries of origin, and several publications via citation and co-citation studies. Finally, the quantity of citations is used to rank the academics (**Table 2**). The table shows the top 15 cited authors in the AI chatbot area from 2005 to 2022.

Table 2. Top Cited Author of AI Chatbot, 2005 to 2022

Rank	Author	Nation	Focus	Number of documents	Scopus citation
1	Araujo, T.	U.S.	Computer science	3	373
2	Nadarzynski, T.	U.K.	Digital health	3	164
3	Yu, S.	U.S.	Customer service	3	146
4	Følstad, A.	Norway	Computer science	5	93
5	Cheng, Y.	China	Customer service	4	78
5	Jiang, H.	China	Customer service	4	78
7	Jin, S. V.	U.S.	Customer service	3	53
7	Wang, X.	Australia	Customer service	3	53
7	Youn, S.	U.S.	Customer service	3	53
10	Yang, H.	South Korea	Computer science	4	40
11	Zhang, Z.	China	Digital health	3	30
12	Shin, D.	South Korea	Computer science	4	27
13	Cheng, X.	China	Customer service	3	24
14	Mou, J.	China	Customer service	4	23
15	Lee, S.	U.S.	Computer science	3	21

The top 5 cited authors of AI chatbots are Araujo, Nadarzynski, Yu, Følstad, and Cheng. Araujo is from the U.S. and is the most cited author. He focuses on human-robot interaction and deep learning in AI. Araujo, Helberger, Kruikemeier, and De Vreese (2020) draw on computer science theories and the growing research on algorithmic appreciation and perceptions to investigate the relationship between individual characteristics and attitudes toward AI-automated decision-making. They concluded that customers worry about the risk of AI chatbot applications and have a neutral attitude toward the usefulness and fairness of AI chatbot applications. Nadarzynski, Miles, Cowie, and Ridge (2019) found that most people online would be open to interacting with a health chatbot, while skepticism about the technology will likely reduce users' willingness. To maximize adoption and utilization, AI-powered health chatbot intervention designers should use a user-centered, theory-based approach to ease patients' fears and improve their experience. In addition, Cheng and Jiang (2020) studied the customer-brand relationship with the AI chatbot application. They extended the TAM model and found that based on the AI users' experience, the customer-brand relationship has mediated with communication quality and customer response.

Co-citation Analysis of the Author

This section employed Author Co-citation Analysis (ACA) to identify the more extensive group of influential academics (**Table 3**). Co-citation analysis pinpoints influential academics who have affected authors (Acedo, Barroso, Casanueva, & Galan, 2006). The results in **Table 3** are notable in a few ways. A co-citation analysis uncovered several academics whose AI chatbot scholars often cite theoretical and methodological publications but have not published them on artificial intelligence for chatbot services.

Table 3. Top Co-cited Author of AI Chatbot, 2005 to 2022

Rank	Author	School of thoughts	Co-citations	Total link strength
1	Følstad, A.	Computer science	139	6952
2	Nass, C.	Computer science	133	6720
3	Sundar, S. S.	Computer science	129	6377
4	Dwivedi, Y. K.	Digital health	108	7261
5	Venkatesh, V.	Computer science	95	6039
6	Araujo, T.	Computer science	94	5207
7	Benbasat, I.	Customer service	89	4727
7	Ko, E.	Computer science	89	4903
9	Davis, F.D.	Customer service	88	5704
9	Grewal, D.	Digital health	88	3551
11	Brandtzaeg, P. B.	Computer science	81	4380
12	Moon, Y.	Computer science	80	4418
13	Hair, J. F.	Customer service	79	3597
13	Kim, S.	Customer service	79	1282
15	Atwell, E.	Customer service	74	2876

Table 3 also stands out for the sheer size of its co-citation sums. As an illustration, three authors, Følstad, Nass, and Sundar, have been cited over a hundred times. Flstad's documents were cited in 24.3% of the 571 documents in the AI chatbot, with 139 co-citations. After Nass, the next best author is Sundar. However, this examination of co-citations shows that the most vital links are not necessarily among the top three co-citations. Dwivedi's "total link strength" is more than any other scholar, demonstrating his outsized influence in this study (**Table 3**). We found that the total link strength of the top 15 authors is above 1,000. However, some authors may have the most co-citations, yet their links may not be as strong as others.

In addition, this statistic tells us that the author Følstad has been widely cited in the Scopus-indexed field of AI chatbots (i.e., total co-citations). Nonetheless, he does not share many citations with other authors in his works (i.e., total link strength). However, Dwivedi has a total link strength of 7,261 thanks to the prevalence with which other researchers mention his many published works.

Furthermore, the author's research into other disciplines provides another practical angle on their influence (Waltman & Van Eck, 2012). Many authors are deeply interested in customer services and the computer science behind AI chatbot applications. However, few authors have explored even a fraction of digital health. The mentioned author mainly focuses on marketing services, computer science, and digital health in his or her research. Analysis of author co-citations is particularly well-suited to elucidating the interconnectedness of different fields (Waltman, Van Eck, & Noyons, 2020).

Intellectual Structure of the AI-related Knowledge Base for the Chatbot Service

The study's final question aimed to tease the "intellectual structure" of the AI chatbot-based knowledge. For this study, we built a co-citation map to illustrate the connections between the 92 researchers who each earned at least 30 citations in the reviewed articles' reference lists (**Table 3**). The relative co-citation frequency of an author is represented by the size of a "node" on a co-citation map. The closeness of nodes represents the frequency with which two authors have "co-cited" one another. Among academics, "links" represent the frequency with which other academics have cited both authors. Finally, VOSviewer groups researchers into "schools of thought," which reflect the knowledge base's underlying intellectual structure (Zupic & Čater, 2015; Waltman & Van Eck, 2012, 2013).

Computer science, digital health, and marketing service are the three main intellectual structures in the literature on artificial intelligence for robot service. It is essential to realize that there are many connections between the three AI for chatbot service schools. Author productivity and citation analyses have already suggested that artificial intelligence is the central topic of study for chatbot service research (Waltman et al., 2010). These connections were mapped using co-citations with a "self-organized" structure (Waltman & Van Eck, 2013).

There are three leading schools of thinking on this topic, the largest of which is held by researchers in the field of computers. This theoretical map is centered on computer science (e.g., Nass, Dwivedi, Venkatesh, and Araujo). As we previously said, several concepts from the field of computer science have found their way into AI. In addition, the digital health field of the co-citation network highlighted smaller "clusters," including Dwivedi and Grewal. There are a total of 31 items here that pertain to studies in the area of digital health. Authors concerned with customer service make up the third school of thought. This group of authors includes Atwell, Liu, Chen, Lee, Zhang, Zhou, and Li, all prominent in their respective fields of AI chatbot application service (**Figure 5**).

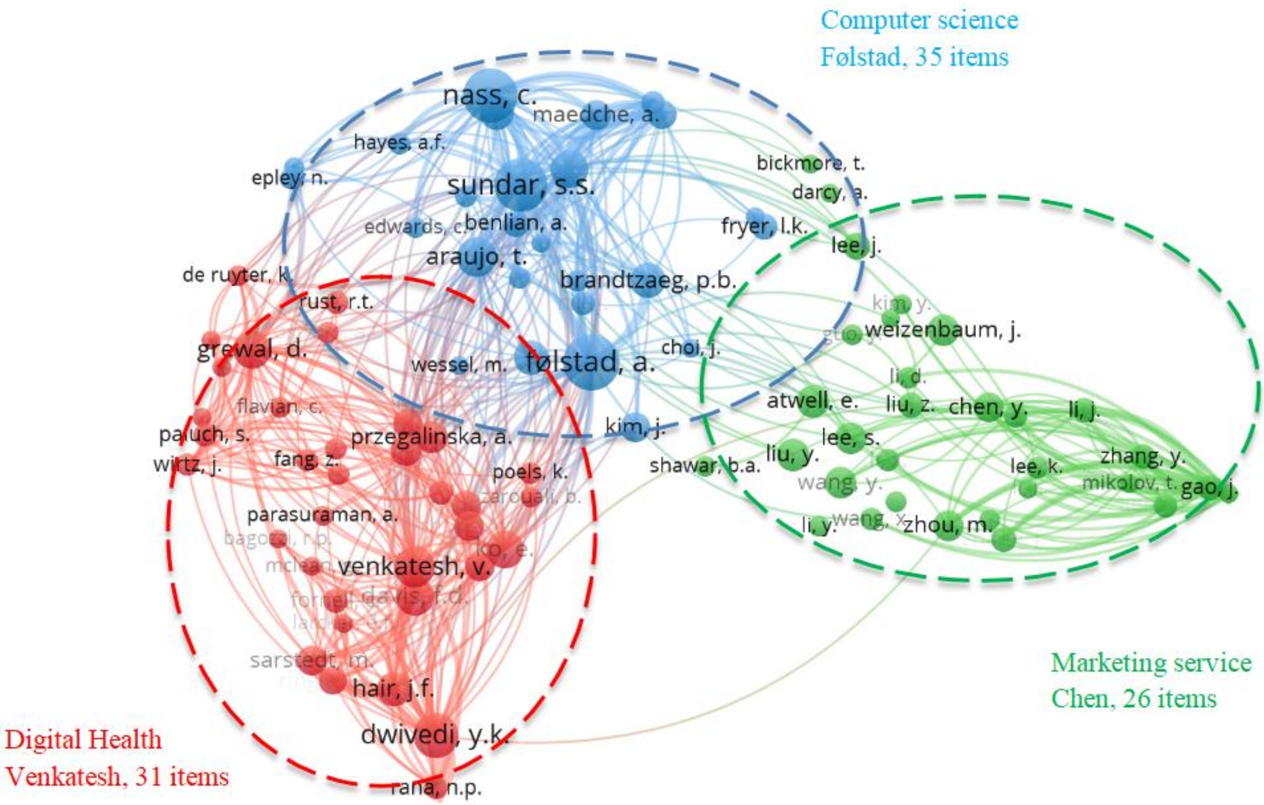

Figure 5. Author Co-citation Map Showing the Schools of Thought on Artificial Intelligence for Chatbot Service (citation threshold 30; display 92 authors)

DISCUSSION

This bibliometric examination aims to identify "self-organized" patterns of knowledge production that develop through time across different fields of study (Zupic & Čater, 2015). This inductive approach aimed to understand the conceptual development of AI for chatbot services. The report looked at the interest in artificial intelligence research in various fields. We can find the related papers extracted in the Scopus database. The most significant document database ever created has benefited several fields, including computer science, digital health, decision science, business, management, and accounting. However, this criterion proved insufficient to resolve this matter due to variations in document identification standards. Hence, we used productivity, citation, and co-citation analysis to learn more about the issue.

Firstly, according to productivity analysis, we could conclude that since 2017, the paper related to AI chatbots has sharply increased, and in the future, they will continue to grow. Then, computer science has undertaken the most significant programmatic research. Indeed, many researchers want to know how intelligent technology (e.g., deep learning, machine learning) is behind the chatbot. Moreover, we also found that authors from the United States have published the most papers (119), then the other Asian countries, such as China, Japan, and India.

Secondly, we used the citation to rank the journals to find which one the authors wanted to contribute to. We found the top 15 journals from the Scopus database. Those journals are reliable sources for researchers wanting to publish a related AI chatbot paper. Besides, the citation analysis also supported the most influential authors, showing that the American author (Araujo) has the most citations. In addition, computer science has had a much more significant impact on artificial intelligence scholarship through citations than scholars in any other discipline.

Thirdly, the author's co-citation analysis offered a graphical depiction of these tendencies. The most frequently referenced authors now receive more than 100 citations. Nevertheless, these schools featured tightly knit communities of scholars, many of whom were frequently mentioned. This proved that there is a sizable "global community of AIC scholars" interested in solving chatbot service issues with AI.

Fourthly, chatbot services have been the primary area of growth for AI over the past decade. AI has been integrated as a central construct in this discipline, as evidenced by the vital citation and co-citation effect among academics. On the other hand, AI seems to be ahead in several ways. It has also been suggested that reviews of science maps can be used to identify "related scholars" or authors who have had a lasting impact on the conversation within a given field of study (Kumar & Reinartz, 2018). Author co-citation analysis, mainly the co-citation map stated above, highlighted the ideas, concepts, and techniques established in artificial intelligence for chatbot services. Chatbot services utilizing AI to respond to customer inquiries are becoming increasingly popular.

Lastly, "AI chatbot application"-related authors had a weak citation impact. To be sure, "co-citation analysis" is the only reason fewer articles focus on AIC research. Evidence of this effect may be seen in the co-citation map, which shows relationships between strategy researchers and those in other fields.

CONCLUSION

This literature study contributes novelly by providing empirical evidence for the philosophical framework of inquiry into "artificial intelligence for chatbot support." The lack of research into AI for chatbot services is unfortunate and can be attributed to the popularity of more niche themes. In addition, the bibliometrics review on AI for chatbot support can only look at one database. Thus, new datasets are required for the bibliometrics review, which analyses the applications of AIC and their outcomes in other fields. As previously mentioned, most AI research is done in computer science, with certain exceptions in marketing. The author hopes that by conducting this analysis, academics will have a clearer picture of the AIC landscape and better pinpoint the authors most relevant to their specific areas of study. According to the author's co-citation map, this is already happening based on patterns in the cited body of work. We expect a similar map to be generated in 10 years to show the expansion and enhanced differentiation of current schools of thought and the increasing density of links between them.

LIMITATIONS

This bibliometric analysis aimed to assess researchers' dedication to studying chatbot services, single out leading lights in the field, and shine a light on fundamental ideas in artificial intelligence. In this section, we will go over the limits of the review, explain how we interpreted the results, and then highlight numerous implications.

Firstly, when compared to more conventional methods of analysis (Arkorful et al., 2020), bibliometrics is limited in its ability to provide light on fundamental concerns such as "whether," "how," and "why" specific methods get better results than others. One bibliometric review's strength is its capacity to summarise overarching trends in a topic and assess the structural aspects of knowledge production (Morgan, 2017). Therefore, it is crucial to emphasize that this analysis goal was restricted to revealing knowledge generation patterns and theoretical trends in artificial intelligence research on chatbot services.

Secondly, the scope of this review was limited, as it would be with any analysis, by the amount of time available to meet the criteria for data analysis. In light of this, the author concedes that the conclusions do not cover the scope of relevant domains, despite the breadth of artificial intelligence addressed in this research. The datasets only covered a limited time because AI for chatbot services is a relatively new field. There are not many papers to review. More work needs to be done in the future to collect data to get a better grasp of "artificial intelligence for chatbot service." As we have already established, using a search strategy is based on a broad term (i.e., artificial intelligence). Several AI-related documents for chatbot services may have been missed because they were not filed under that heading.

Lastly, this evaluation uses a bibliometric approach to look at frequent occurrences in the literature (e.g., highly cited authors). This is based on the belief that locating influential research might help bring attention to important concepts. However, it is possible to miss both emerging trends that have not yet received many citations (Huang & Rust, 2018) and competing viewpoints that have not yet won over most of the community.

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