Bibliometric Analysis and Systematic Review of Research on Expert Finding: A PRISMA-guided Approach

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Abstract: *This study conducts a comprehensive exploration of expert retrieval using a dual approach of bibliometric analysis and systematic review, guided by the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) methodology. From 2000 to 2023, our investigation reveals a notable upward trajectory in expert locating study, focusing on 494 articles identified from Scopus using specific keywords related to Expert Finding (EF) and Expert Finding Systems (EFSs). Through bibliometric analysis, utilizing VOSviewer, we identify prominent co-author groups, highly-cited documents, and global participation, shedding light on the collaborative and internationally expansive nature of EF investigations. Keyword co-occurrence and text analysis reveal thematic clusters, signaling the evolving emphases in the field from foundational expert search tasks to considerations of platform interactions. Simultaneously, our systematic review, conducted on a subset of 51 articles using NVivo, explores domains seeking expert solutions, prevalent datasets, and common evaluation methods. This research not only synthesizes the current state of EF and EFS literature but also charts a course for future exploration, contributing to a deeper understanding of the field and guiding the trajectory of forthcoming research endeavors*.

Keywords: *Expert finding, expert finding systems, bibliometric analysis, systematic review, PRISMA methodology*.

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1. Introduction

In the rapidly evolving landscape of information retrieval and knowledge dissemination, the identification and mobilization of expertise play pivotal roles in fostering innovation and problem-solving. Expert Finding (EF) and Expert Finding Systems (EFSs) have emerged as indispensable tools, facilitating the efficient location of individuals with specialized knowledge and skills. As the demand for expertise, an understanding of the trends, challenges, and advancements in the field of EF becomes essential. This comprehensive review utilizes on a dual methodology employing bibliometric analysis and systematic review to examine the expansive body of research on EF. The integration of these approaches is guided by the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) methodology, ensuring a rigorous and transparent investigation. The period under consideration spans from 2000 to 2023, encapsulating the dynamic evolution of EF research.

The motivation behind this review stems from the recognition of the escalating importance of EF across various domains and the necessity to extract insights from the expanding literature. When seeking a comprehensive understanding of a particular issue, one of the quickest approaches is to look at review papers. In the realm of EFs, several systematic reviews are worth noting, notably those conducted between 2017 and 2019. Lin *et al*. [30] conducted a comprehensive review of expert search techniques in 2017, unveiling that data collection about experts primarily stems from three channels: Meta databases, document collections, and referral networks. The models employed for expert identification encompass generative probabilistic models, voting models, graph-based models, and hybrids. Noteworthy test data collections such as W3C, CERC, UvT, DBLP, and CiteSeer were also mentioned. In 2018, Amjad *et al*. [4] delved into methods for ranking academic authors within the domain of academic social networks, analyzing documents spanning from 1999 to 2017. Three prominent author ranking methods were identified, namely link analysis, text similarity, and learning-based approaches. The review also highlighted various datasets and evaluation measures across these categories. However, this article exclusively focuses on the specific task of EF and ranking objects, applied specifically to the academic field. Yang *et al*. [57] explored expert recommendation in Community Question Answering (CQA), categorizing existing studies into three main areas: profile modeling, expert recommendation methods, and the impacts of expert recommendation. The article presented a comprehensive descriptive framework within the CQA domain, considering relevant articles published from 2008 to 2019.

Notably, all three aforementioned review papers concentrate on singular aspects (techniques) or specific fields (ranking of academic authors or CQA expert recommendations) and lack a comprehensive exploration across diverse fields and tasks.

Husain *et al*. [26] conducted a systematic literature review in 2019, focusing on EFSs and expertise-seeking studies based on documents published between 2010 and 2019. This study scrutinized five key aspects: the domains of EFSs, expertise sources, methods, and datasets, the distinctions between expertise retrieval and seeking, and contextual factors. Additionally, the review identified five gaps in EFSs corresponding to the aforementioned issues. This review seems to be the most thorough survey of EFSs.

The absence of thorough reviews from 2019 to 2023 is a glaring gap in the expert finding field. With the accelerated advancements and the integration of numerous new technologies into this domain during these years, there is a critical need for additional comprehensive assessments of this field. As organizations increasingly rely on the collaborative power of experts to address complex challenges, understanding the trajectories of EF research becomes instrumental in shaping the future of information retrieval systems. Moreover, aspects like reviewing research trends, co-citations, and co-authors commonly evaluated in bibliographic reviews are rarely explored in this field.

By leveraging bibliometric analysis of 494 articles, we aim to uncover trends in co-authorship, bibliographic coupling across countries, and the global landscape of EF investigations. Simultaneously, our systematic review, focused on a subset of 51 articles, delves into the specific domains seeking expert solutions, prevalent datasets employed in expert search tasks, and the evaluation methods shaping the assessment of expert finding effectiveness. Explicitly, this review addresses three key Research Questions (RQs): Firstly, we inquire into the domains that frequently engage with EF, shedding light on the diverse contexts in which expertise identification is paramount RQ1. Secondly, we examine the datasets commonly utilized in expert search tasks, recognizing the foundational information upon which these systems operate RQ2. Lastly, we explore the evaluation methods employed to assess the efficacy of EF and EFSs, contributing to a critical appraisal of their performance and impact RQ3.

2. Methodology

2.1. PRISMA Methodology

This systematic review adheres to the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) guidelines. Inclusion criteria for the review were defined based on the relevance of articles to Expert Finding (EF) within the timeframe of 2000 to 2023. To ensure a comprehensive representation of the literature, the following keywords were employed: "expert finding system," "expert find*," "expert locate*," "expert rank*," "expert search" and "expertise retrieval." Additionally, the search was restricted to specific domains, including EF, expert search, recommender systems, expertise retrieval, expert rankings, and EFSs.

The exclusion criteria involved studies outside the defined timeframe, languages other than English, and articles not directly related to EF. The document types considered for this systematic review encompassed Articles, Books, Book chapters, Conference papers, and Reviews. The search was restricted to the Scopus database, resulting in the identification of 494 articles. Two reviewers independently screened each record and report retrieved. They worked independently to ensure reliability. Any discrepancies between the two reviewers were resolved through discussion. The process involved reading titles/abstracts/keywords and decisions on whether to collect data were made based on the predefined inclusion criteria. Additionally, each report identified was cross-checked for inclusion against the predefined criteria.

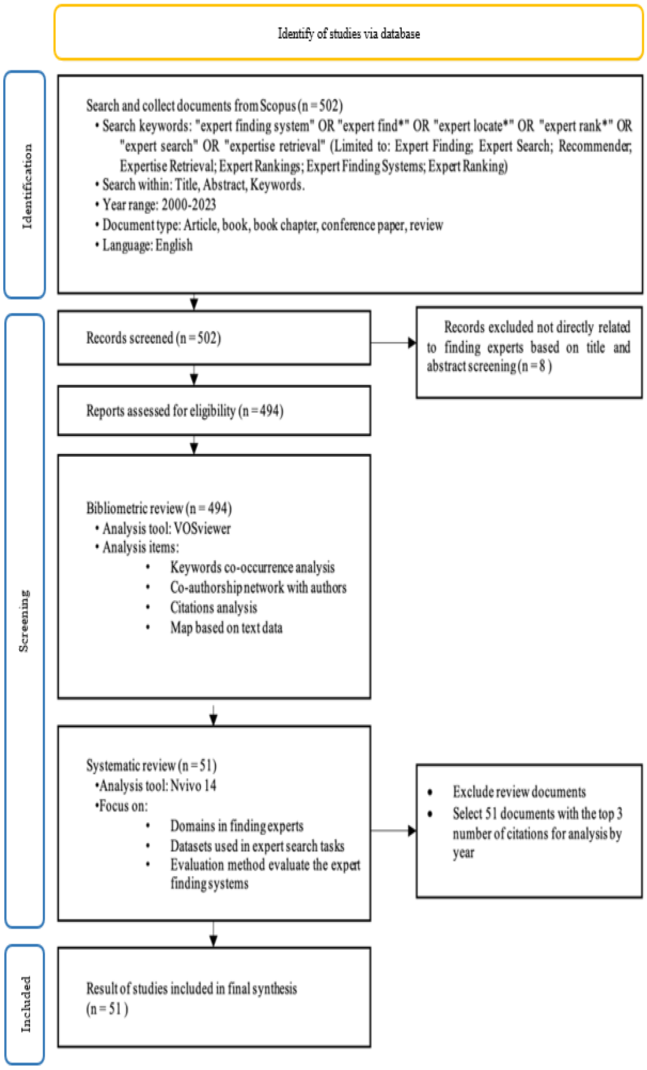


Figure 1. PRISMA edited flow diagram.

The data collection and analysis process is shown in Figure 1 above. This dual approach, incorporating both:

1. Bibliometric analysis.
2. Systematic review, guided by the PRISMA methodology, provides a comprehensive understanding of the current state of EF literature and informs future research directions in the field.

2.2. Bibliometric Analysis Using VOSviewer

Our bibliometric analysis, revealed trends through keyword co-occurrence analysis, identified prominent co-author groups, explored bibliographic coupling across countries, and visually mapped the global landscape based on text extracted from abstracts and titles. To conduct the bibliometric analysis, we utilized VOSviewer [51]. This tool was employed to identify trends based on keyword co-occurrence analysis, co-author groups, bibliographic coupling across countries, and to create a map based on the abstracts and titles of the identified articles [52]. VOSviewer allows us to visually represent the collaborative and international nature of EF investigations. Keywords were extracted from the articles and analyzed for co-occurrence, shedding light on evolving emphases in the field. The co-authorship network was examined to identify prominent author groups, highlighting collaborative patterns. The generated map visually represents the interconnectedness of research themes, providing insights into the structure and dynamics of the field.

2.3. Systematic Review Using NVivo

Based on their highest citation counts among the identified pool of 494 articles, we selected 51 papers from the top 1 to 4 articles per year for the systematic review. This subset will be analyzed in detail to address three key Research Questions (RQs): the domains frequently engaging with EF (RQ1), the commonly used datasets in EF tasks RQ2, and the evaluation methods employed to assess the efficacy of Expert Finding Systems (EFSs) RQ3. For the content analysis, Nvivo software was employed [1]. This phase focused on answering three key RQs:

1. What domains frequently engage with EF?
2. Which datasets are commonly used in expert search tasks?
3. Which evaluation methods are employed for assessing the effectiveness of EFSs?

Data extraction involved coding relevant information from each article, including domains, datasets, and evaluation methods. Multiple reviewers worked independently to ensure reliability, and any discrepancies were resolved through discussion [38]. NVivo facilitated the systematic organization and analysis of textual data, ensuring a thorough exploration of the content [41]. The results obtained from NVivo were synthesized to provide comprehensive insights into the diverse domains, datasets, and evaluation methods prevalent in the field of EF.

3. Result

3.1. Number of Publications Related to EF

We conducted a statistical analysis of research articles in the EF field, extracted from Scopus from 2000 to 2023 (see Figure 2).

Figure 2. Number of publications related to EF.

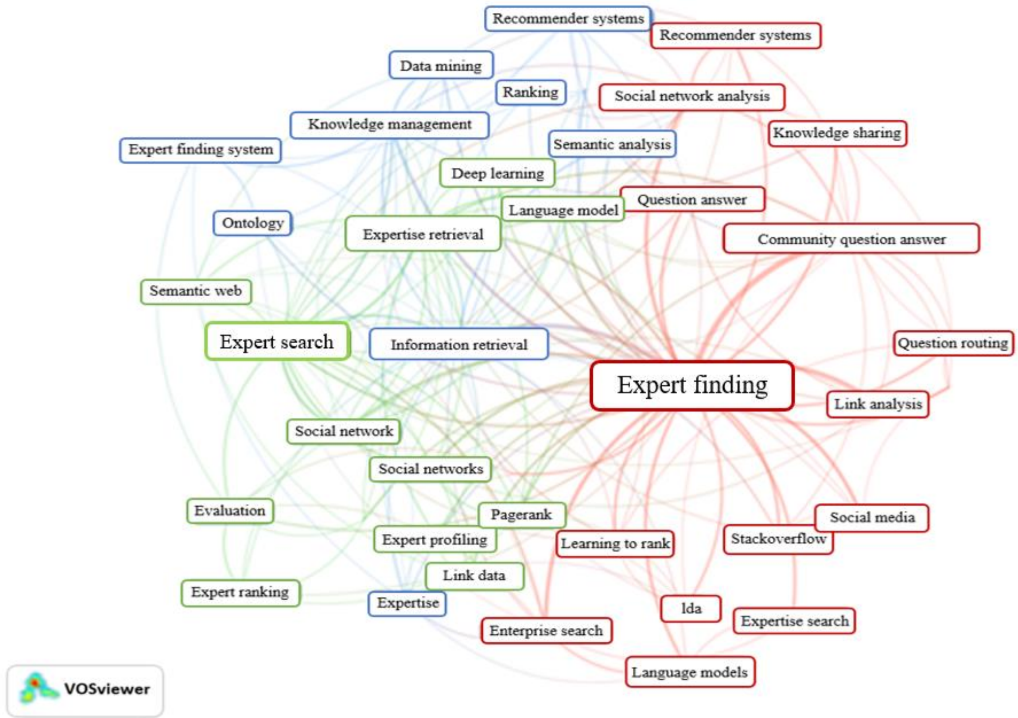
The data reveals that between 2000 and 2005, there was a relatively modest output of research in this domain. However, a noticeable shift occurred from 2006 to 2011, with articles escalating from 4 to 33 annually. Subsequently, from 2011 to 2021, the publication rate remained relatively constant. In 2023, the number of articles was slightly lower, possibly because some articles have not been indexed into the Scopus database.

Based on the proportion of articles each year, we identified the top 1 to 4 articles per year based on the highest citation counts (represented by the orange line). These selections, totaling 51 documents, were chosen for their relevance to the RQs, prompting a thorough examination and in-depth analysis to uncover overarching themes and insights.

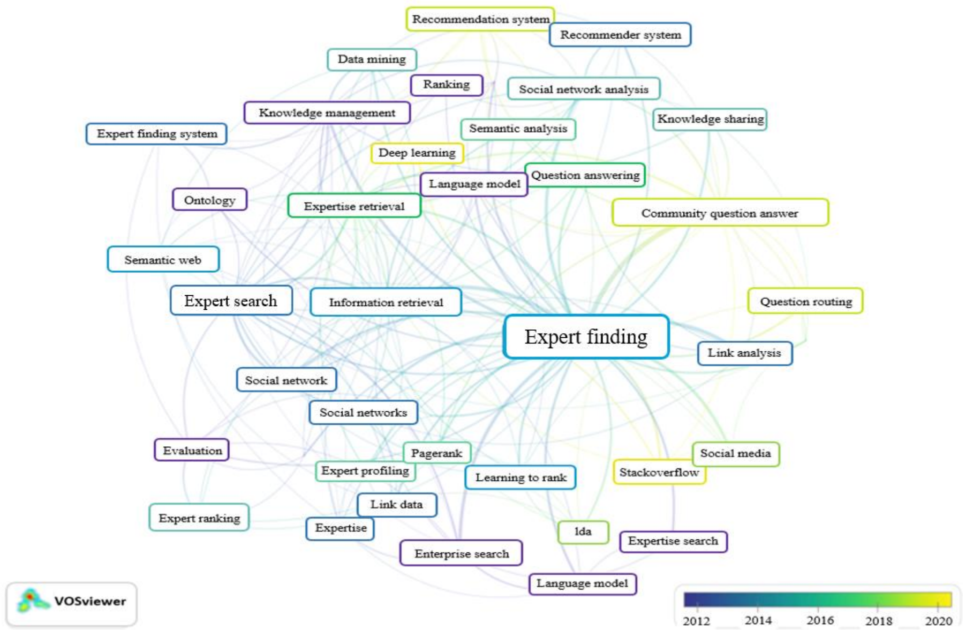
3.2. Bibliometric Review

Trends based on keywords co-occurrence analysis. A total of 1008 keywords (author keywords) were investigated, 40 of which appeared more than 5 times.

Figure 3-a) shows the visual network map of keywords co-occurrence. Nodes in different colors represented different types of clusters, node size represented the occurrence of keywords, and a thick connection line showed a close relationship between two items.



a) Visual network map of keywords co-occurrence.



b) Visual network map of keywords co-occurrence by year.

Figure 3. Keywords co-occurrence map.

The top three keywords (exclude searching keywords) were "information retrieval" with 33 occurrences, "Community Question Answering (CQA)" with 32 occurrences, and "knowledge management" with 21 occurrences.

Figure 3-b) depicts the visual network map illustrating the co-occurrence of keywords over the years. In 2012 and earlier, main keywords included "enterprise search", "language models", and "knowledge management". Contrastingly, in the

2020s, prominent keywords shifted towards CQA, “Stack overflow”, and “deep learning”. This shift indicates a transformation in research focus within EFs, aligning with the emergence of new platforms and techniques.

The shift in prominent keywords over the years indicates a transformation in research focus within EFs, driven by several factors. The emergence of new technologies and platforms, such as community question-answering platforms like Stack Overflow, has prompted researchers to explore real-world problems and adapt methodologies to the evolving technological landscape. This shift signifies a growing emphasis on user-centric research, with a focus on practical, user-oriented problems. Additionally, the availability of vast amounts of data from community platforms has underscored the value of big data analytics, leading to a recognition of the collaborative and social aspects of information sharing and problem-solving. Researchers are increasingly leveraging advanced machine learning techniques, particularly deep learning, for practical applications, reflecting changing demands and trends in the field. Overall, this dynamic shift towards more socially oriented and practically impactful research aligns with the evolving landscape of information sharing and technological advancements in the 2020s.

Table 1. Description of major keywords in each cluster.

Cluster	Main keywords	Occurrences	Total link strength	Theme description
Cluster 1 (Red)	EF	233	155	EF and domain
	Expertise search	66	35	
	Community question answer	32	31	
	Social media	18	17	
	Enterprise search	16	16	
	Link analysis	13	13	
	Social networks analysis	12	12	
	Language models	11	11	
	Question answering	8	8	
	Stackoverflow	7	7	
Cluster 2 (Green)	Expert search	66	35	Tasks in expert search
	Expertise retrieval	39	27	
	Social networks	16	15	
	Language model	11	11	
	Evaluation	7	7	
	Page rank	8	8	
	Linked data	6	6	
	Expert profiling	5	5	
	Expert ranking	14	4	
Cluster 3 (Blue)	Information retrieval	33	32	EFS and related issues
	Ontology	21	20	
	Knowledge management	21	20	
	Data mining	10	9	
	Expertise modelling	6	6	
	Expertise	5	5	
	Semantic analysis	5	5	
	Expert finding system	8	4	

There are three main clusters, including the following:

1. EF and domain.
2. Tasks in expert search.
3. Expert finding system and related issues.

Table 1 shows the number of occurrences, total link strength and theme description of each cluster. According to the results of cluster analysis, these keywords were divided into three clusters.

The three identified keyword phrases delineate the primary themes frequently explored by authors in the realm of expert search. Specifically, cluster 1 (red) highlights domains that are commonly of interest to those looking for expert information, expertise, or expert relationships. These include areas like CQA, social media, enterprise search, social network analysis, and platforms like Stack Overflow. These are areas that need experts to answer issues that users are interested in, share knowledge on social networks, and contribute to problem-solving within enterprises [8, 39, 49]. Moreover, these environments also serve to discern an expert’s expertise and relationships.

Moving on to cluster 2 (green), it focuses on the core tasks integral to expert search, such as expert retrieval, data linking, expert profiling, language models, expert ranking, and evaluation. Expert retrieval stands out as a crucial initial step in the search process. Subsequently, data collection necessitates linking information and creating expert profiles. Models are employed to identify suitable experts in various fields, execute expert rankings, and assess outcomes. Noteworthy techniques like page rank, deep learning, and semantic web are commonly applied to fulfill these tasks [22, 34, 43].

Lastly, cluster 3 (blue) directs attention to the Expert Finding System (EFS) and related issues. EFS is a system in the field of information retrieval. Stages such as data mining, using ontology, and semantic analysis to handle expert information. Techniques like expertise modeling and ranking are integral components associated with expert search systems [11, 54].

- **Co-Authorship Network with Authors**

When conducting co-authorship analysis with the unit of analysis being authors, the maximum number of authors per paper was 25, and the minimum number was 5. Among the 1251 authors identified, only 26 met the specified thresholds.

These authors were then categorized into 11 distinct clusters. The findings, presented in Table 2, highlight that the author “De rijke, Maarten” has 3 links, contributed to 13 documents, and accumulated a total of 16 link strengths. Similarly, author “Balog, Krisztian” is connected with 2 links, contributed to 15 documents, and accumulated 15 total link strengths. Upon further investigation, we discovered 11 papers in which the aforementioned two authors collaborated as co-authors. The strong interconnection among these authors becomes evident when delving into research within the domain of expert search.

Table 2. Co-authorship network with authors.

Author	Documents	Citations	Total link strength
de campos, luis m.	8	43	16
de rijke, maarten	13	1072	16
fernández-luna, juan m.	8	43	16
huete, juan f.	8	43	16
balog, krisztian	15	1118	15
hiemstra, djoerd	9	176	12
king, irwin	6	306	11
lyu, michael r.	6	306	11
deng, hongbo	5	257	10
macdonald, craig	13	445	10
ounis, iadh	10	384	10
beigy, hamid	7	117	8
bogers, toine	7	223	8
neshati, mahmood	11	180	8
serdyukov, pavel	8	144	6
li, juanzi	8	213	5
liu, hongtao	5	15	5
peng, qiyao	5	15	5
boeva, veselka	5	18	4
tsiporkova, elena	5	22	4
tang, jie	9	311	3
daud, ali	6	228	2

Table 3. The top 10 documents with the highest number of citations.

Topic	Title	Authors and Document	Year	Total citations	Rank
Model for EF	Formal models for EF in enterprise corpora	Balog *et al*. [7]	2006	457	1
	A language modeling framework for EF	Balog *et al*. [6]	2009	184	4
	Probabilistic models for EF	Fang and Zhai [20]	2007	146	9
	Formal models for EF on DBLP bibliography data	Deng *et al*. [17]	2008	133	10
Online knowledge communities and CQA	Finding experts in community-based question-answering services	Liu *et al*. [32]	2005	170	5
	ExpertRank: a topic-aware EF algorithm for online knowledge communities	Wang *et al*. [54]	2013	169	7
	EF for question answering via graph regularized matrix completion	Zhao *et al*. [60]	2015	150	8
Others	Social network analysis and mining for business applications	Bonchi *et al*. [9]	2011	250	2
	Voting for candidates: adapting data fusion techniques for an expert search task	Macdonald and Ounis [35]	2006	207	3
	Mining advisor-advisee relationships from research publication networks	Wang *et al*. [53]	2010	170	6

- **Citations Analysis**

With 494 documents, there are 46 documents cited more than 40 times. Table 3 lists the 10 documents with the highest number of citations.

The analysis reveals that among the top 10 documents with the highest number of citations, the majority (4 out of 10 articles) are studies focusing on the model for EF. In which, “Formal models for EF in enterprise corpora” is the most citation paper. The article centers on two expert-finding models. In model 1, candidate models are employed to identify a candidate’s expertise, whereas model 2 utilizes document models to ascertain a candidate’s areas of expertise. Following closely are articles related to Online knowledge communities and CQA, constituting 3 out of the top 10. Notably, it is interesting to observe that EF within the domain of CQA has emerged as a novel research topic in the years from 2020 onwards. However, it is noteworthy that Liu *et al*. [32] have been researching this topic since 2005, highlighting the author’s early foresight in this field.

- **Map Based on Text Data**

When building a map based on text with fields from which terms will be extracted from abstract and title, there are 8123 terms, minimum number of occurrences of term is 20, we found 101 terms. Among them, there will be 61 terms to be selected that have the most relevant terms. (see Figure 4).

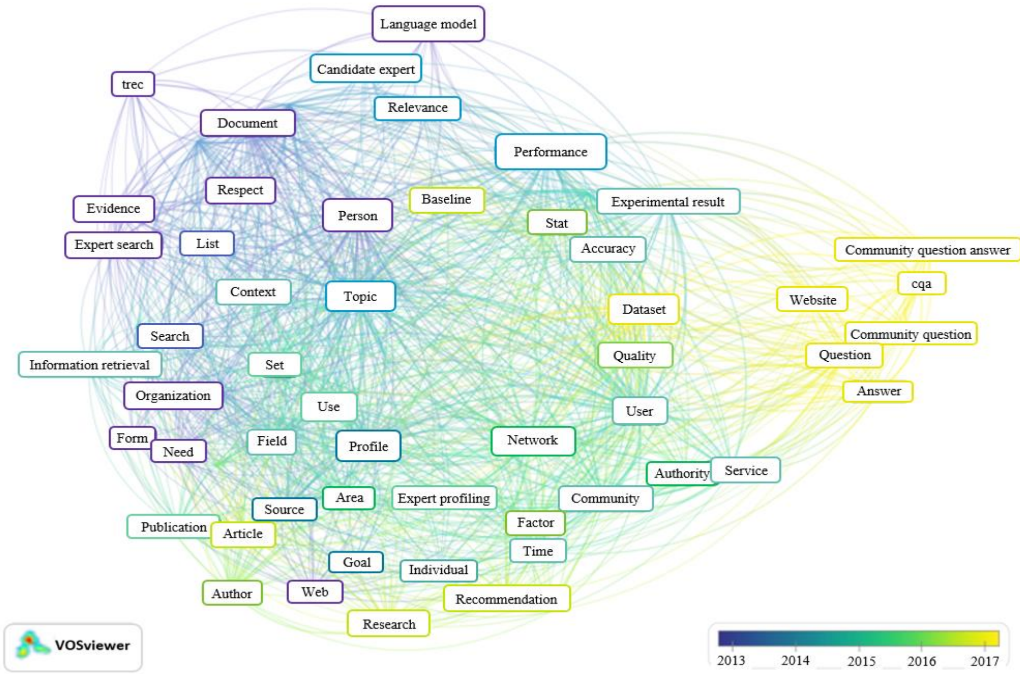


Figure 4. A map based on text data extracted from abstract and title.

Four temporal clusters can be delineated as follows:

- Years 2000 to 2013 (purple): emphasis on the expert search task and the enterprise track (TREC)/organization.
- Years 2014-2015 (dark green): concentration on query analysis and returned results, encompassing topics such as performance, relevance, profile, source, candidate expert, experimental results, and accuracy.
- 2016s (light green): centered on the analysis of articles and researchers in the academic field, incorporating factors such as recommendation, articles, researchers, and baseline.
- 2017 onwards (yellow): focused on datasets, websites, question and answer communities, and interactivity on these platforms, involving elements like dataset, website, community answering question, answer, question, and community question.
- This clearly shows the main research trend in the expert search domain, transitioning from a focus on the enterprise sector to academia and online platforms, particularly those dedicated to CQA.

3.3. Systematic Review

We will focus on answering the 3 RQs mentioned in the previous section.
What domains are often interested in finding experts? (RQ1).

EF tasks have garnered interest across diverse fields, necessitating the identification of detailed tasks and the associated challenges. Through a search of information in 51 highly cited research articles spanning from 2000 to 2023, the authors have identified six prominent areas frequently mentioned in expert search tasks. These include:

- Academic: this domain encompasses various tasks associated with EF, including finding experts for consultation in new research endeavors, automated assignment of papers to reviewers in peer-review processes, recommendation of reviewer panels for state research grant applications, locating advisors and supervisors, finding experts (of the university) for collaborative projects, and fostering research collaboration. These tasks address the recurring needs of organizations operating in the academic sector, such as universities, research institutes, conferences, and journals, underscoring the essential nature of expert identification in this field. These studies primarily concentrate on the timeframe spanning 2006 to 2012, highlighting the early attention given to expert search within the academic domain. Nevertheless, there appears to be a decline in interest in more recent years.
- Enterprise: research conducted from 2000 to 2011 focused on finding experts in the enterprise field, particularly within large businesses and organizations with substantial workforces. These publications marked the initial phase of comprehensive exploration in the field of expert search, with notable contributions from studies by Balog *et al.* [5, 6, 7, 8] and the utilization of TREC datasets from 2005 to 2008. Tasks outlined in these studies encompassed finding experts for projects, collaborations, answering questions, diagnosing complex system problems, sharing knowledge, and seeking experts for consultation.

However, some gaps became evident, such as the article's exclusive focus on finding experts within large enterprises with limited consideration for seeking external experts. Besides, the research conducted was relatively dated, and there has been a shortage of recent studies. Considering the significant changes in businesses' needs due to technological and market developments, the current lack of new research on finding experts in the corporate sector represents a noteworthy gap that researchers could consider.

CQA: this emerging field, particularly prominent from 2019 to 2023, has captured authors' attention when researching issues related to finding experts. The distinguishing feature of this platform lies in its ability to accommodate a multitude of questions spanning various domains and difficulty levels. Consequently, identifying experts who can answer these questions most accurately is crucial. Consequently, delving into the CQA domain has become an enticing avenue for researchers. Some of the tasks we identified in the literature are: finding experts to answer target questions and to promote the process of knowledge sharing; identifying the group of experts; meeting the scientific needs and providing the expert workforce for organizations; and finding the candidate experts for jobs. Moreover, certain studies have yet to describe explicit tasks. It can be seen that the new domain indicates a novel trend previously not yet mentioned much in reviews, such as Husain *et al*. [26].

Social network: this domain also captivates the attention of the expert-finding research community, although the volume of articles within this field is not as high as those of previously mentioned domains. Specific tasks gleaned from the literature include: finding experts for collaboration; responding to factual questions; providing recommendations on products, people, or places; performing generic tasks; and finding local experts. Social networks frequently serve as tools for uncovering social connections or extracting expert-related information from posts on experts' pages.

Table 4. Finding expert's domains.

Domain/field	Task	References
Academic (e.g., a university context)	Finding experts for consultation when doing new research	[17]
	Assigning papers to reviewers automatically in a Peer-Review Process	
	Recommending panels of reviewers for state research grant applications	
	Finding advisors	[53]
	Finding a supervisor	[2]
	Find experts (of the University) for joint projects	[11]
	Research collaboration	[7, 11, 27]
	Knowledge sharing	[8]
Academic social networking	Collaboration and innovation in the research Sharing and exchange of academic expertise	[56]
CQA	Finding experts to answer target questions and to promote the process of knowledge sharing	[23, 24, 31, 39, 42, 46, 59, 63]
	Identify the group of experts	[32]
	Meeting up the scientific needs and Providing expert workforce for organizations	[15]
	Finding the candidates experts for jobs	
	No specific task	[16, 19, 34, 40, 61]
Enterprise/Organisations	Finding experts for project	[7, 44]
	Finding experts for collaboration	[9, 36]
	Finding experts to answer a questions	[28]
	Finding experts to problem diagnosis of complex system	[48]
	Sharing expertise	[14]
	Specialist to consult	[7]
	No specific task	[5, 6, 18, 20, 21, 35, 45, 58]
Online knowledge communities	Knowledge sharing and seeking	[33, 43, 54]
	Find experts to help solve technical problems	[40]
Social network	Finding experts for collaboration	[22, 47]
	Responses to factual questions	[10]
	Providing recommendations upon products, people or places	
	Performing generic tasks	
	Finding local experts	[13]
	No specific task	[16]

Online knowledge communities and Academic social networking: Among the 51 documents we utilized for summarizing research, these are the two domains with the least number of referenced articles. Within these domains, we identified key tasks associated with expert searching, including knowledge sharing and seeking, addressing technical issues in online knowledge communities, fostering collaboration and innovation in research, and facilitating the exchange of academic expertise in academic social networking. While the documentation supporting these domains in expert search research is limited in our review, their significance cannot be overlooked. Platforms such as Google Scholar and ResearchGate serve as extensive research communication hubs, aggregating information from academic experts globally. Similar to online knowledge communities, these platforms are vital for the widespread sharing of knowledge among diverse users. Consequently, these domains remain integral in the process of EF.

As per Table 4, CQA and enterprise stand out as the most frequently referenced domains among the studies, each accounting for a 32.6% rate. Academics is the next most popular domain at 15.2%, closely followed by social networking at 10.8%. Lastly, online knowledge communities and academic social networking rates are 6.6% and 2.2%, respectively.

A distinctive feature of this review is the explicit delineation of tasks associated with respective domains, which previous reviews did not distinctly emphasize

- Which datasets are commonly used in expert search tasks? (RQ2)

In research on finding experts, the experimental setups and the result evaluation of the results are essential components. Researchers, based on the specific objectives and tasks associated with expert searching, will opt for the most fitting dataset collections.

Table 5. Expert search tasks's datasets.

Dataset	Platforms	Environment	Year	Data size	Studies used the dataset
CQA websites	ByteCup	CQA	2002-2005	290,000 question	[59]
	Wondir		2002-2005	852,316 QA pairs	[32]
	Yahoo! answers		2007-2008	216,563 - 237,083 question; 593,107- 1,9 million answers	[61, 62]
	Stack overflow		2008-2018	128,217-1,5 million questions; 2,8 million answers;	[15, 23]
	Stack exchange		2009-2014	24,120,523 posts; 3,401 questions; 5300 users	[34, 42]
	Tianya wenda		2008-2010	1.3 million questions; 5.5 million answers; 274,896 users	[62, 63]
DBLP		Academia	2007-2008	955,000-1,1million papers; 574,000 - 654,628 authors	[7, 16, 27, 29, 53]
EventSeer.net		Academia	-	16821 events - 522938 authors	[29]
Google Scholar		Academia	-	953,774 papers - 574,369 authors	[17]
LexR		Academia	-	-	[27, 37]
MAS		Academia	-	32,548 papers - 63,993 authors	[12]
Microsoft office discussion groups		Enterprise	2005-2007	-	[54]
NUCATS		Academia	2009	83,213 papers-15,592 authors	[22]
PubMed		Academia	2017	26,759,991 papers	[3]
Self-collected dataset	Academic social network sites (ResearchGate)	Academia	2019	>15 million users	[56]
	Amazon mechanical turk	Enterprise	-	15 million geo-tagged Twitter lists; 2,000 judgments	[13]
	Public social networks (Facebook, LinkedIn, and Twitter)	Social network	-	40 people; 230,000 information resources	[10, 55]
	Quora	CQA	2012-2013	444,138 questions; 887,771 answers; 95,915 users	[60]
	Real online community	CQA	2009-2010	119,831 threads; 721,531 posts; 91,795 members	[33]
	Reddit	CQA	2020-2021	1,100 comments	[46]
	ScholarMate	Academia	-	200M and 500M	[47]
	Survey from internal company	Enterprise	-	1,832 members; 36,000 profiles	[28]
Thomson reuters WoS		Academia	2009	83,213 papers; 15,592 authors; 38,656 keywords	[22]
TREC	TREC 2005, 2006	Enterprise	2005-2006	1092 candidate experts; 49-50 topics/queries	[5, 7, 35, 36, 44]
	TREC 2007		2007	3500 candidates; 50 queries	[21, 44]
	TREC 2008		2008	1092 candidate experts; 77 queries	[21]
TU		Academia	-	-	[11]
UvT		Academia	-	38,422 papers; 1,168 experts; 30 queries	[8, 45]

Table 5 systematically provides a comprehensive overview of commonly utilized datasets in expert search tasks, detailing platforms, environments, years, and frequency of usage for each dataset. Notably, datasets originating from CQA websites like ByteCup, Wondir, Yahoo! Answers, Stack Overflow, Stack Exchange, and Tianya Wenda, spanning from 2002 to 2018, have been extensively employed in 10 studies, shedding light on question and answer platforms. Additionally, academia-centric datasets such as DBLP, EventSeer.net, Google Scholar, LExR, Microsoft Academic Search (MAS), NUCATS, PubMed, Thomson Reuters WoS, TU, and UvT, with specified platforms and usage years, are discussed. The versatile Self-collected Dataset, drawn from academic social networks, Amazon Mechanical Turk, public social networks, Quora, online communities, Reddit, ScholarMate, and company surveys, spanning various environments from 2009 to 2021, has been utilized in 9 studies, offering insights into academia, enterprise, social networks, and Q and A websites. The TREC dataset, rooted in the enterprise environment from 2005 to 2008, has a significant frequency of 6 studies. We found datasets from CQA platforms and self-collected datasets that were not included in the studies by Lin *et al*. [30], Amjad *et al*. [4], and Husain *et al*. [26]. While prior studies focused on well-known CQA platforms like Yahoo! answers or stack overflow, our literature review has revealed previously unexplored datasets such as Tianya Wenda, ByteCup, Stack Exchange, and Wondir. This expansion in dataset recognition is also mirrored in the inclusion of self-collected datasets, contributing to a more comprehensive understanding of the available data set in the field.

- Which evaluation method is used to evaluate the EFSs? (RQ3).

The findings about the evaluation methods employed for assessing EFSs are elucidated in Table 6. The table encompasses a diverse array of evaluation metrics, each associated with the number of studies utilizing that specific metric.

Table 6. Evaluation metrics.

Evaluation metrics		Number of studies using metric	References
Information retrieval metrics	Precision; R-precision; mean R-precision; mean Pr	23	[3, 7, 11, 13, 14, 16, 17, 19, 21, 22, 24, 27, 31, 35, 36, 40, 42, 44, 45, 53, 54, 60]
	Mean Average Precision (MAP)	22	[2, 5, 6, 7, 8, 10, 11, 16, 17, 19, 20, 21, 31, 35, 36, 40, 44, 45, 53, 61, 62, 63]
	Mean Reciprocal Rank (MRR)	21	[5, 6, 7, 8, 10, 11, 15, 16, 21, 24, 28, 31, 32, 42, 44, 45, 54, 60, 61, 62, 63]
	Normalized Discounted Cumulative Gain (NDCG)	12	[10, 11, 13, 15, 24, 33, 34, 46, 53, 55, 59, 60]
	Recall	4	[2, 12, 18, 54]
	Accuracy	3	[34, 46, 60]
	Aspect-based Relevance Calibration (ARC)	1	[22]
	Area Under the Curve (AUC) [25]	1	[46]
	Binary Preference (Bpref)	1	[17]
	Expected Reciprocal Rank (ERR)	1	[15]
	Macro-average F-measure(Ma); Micro-average F-measure(Mi)	1	[54]
	11-P curve	1	[45]
	Average Precision at K (Avg. P@K)	1	[10]
Qualitative	Human judgement based	2	[47, 63]
Regression metrics	R^2 Score Mean Absolute Error (MAE)	1	[46]
Rank correlation	Kendall's	1	[33]
	Spearman's	2	[33, 43]

The predominant focus is on information retrieval metrics, with a significant number of studies utilizing metrics such as Precision (23 studies), MAP (22 studies), MRR (21 studies), NDCG, recall, accuracy, and so on. This comprehensive set of metrics reflects the multifaceted nature of evaluating EFSs considering factors such as precision, recall, and information retrieval performance. Moreover, the inclusion of qualitative metrics, specifically those based on human judgment, in two studies emphasizes the recognition of subjective assessment in evaluating the effectiveness of EFSs. The presence of regression metrics, namely R2 Score and MAE, in one study, indicates a consideration for quantitative regression analysis to assess system performance. Lastly, the incorporation of rank correlation metrics such as Kendall's and Spearman's in two studies underscores the importance of understanding the ranking consistency of EFSs.

4. Conclusions

Our study offers a thorough examination of the evolving landscape in EF research through a combination of bibliometric analysis and systematic review using the PRISMA methodology. Through bibliometric analysis conducted with VOSviewer, we uncovered collaborative trends and thematic clusters reflecting the shifting emphasis in the field, particularly towards academia and online platforms like community question answering. Our systematic review of 51 articles, utilizing NVivo, delved into EF domains, prevalent datasets, and evaluation methods, addressing key RQs and highlighting a transition from enterprise to academia and community platforms. Additionally, we provide detailed insights into specific tasks associated with expert search in each domain, enhancing scholarly discourse by covering recent developments from 2019 to 2023, a timeframe overlooked in prior reviews.

- **Limitation**

While this study has yielded novel findings, it is imperative to acknowledge certain limitations. Firstly, the data about publications in the domain of EF was exclusively sourced from the Scopus database; thereby, data from other relevant search sources such as WoS, ACM, or IEEE Xplore were omitted. Despite this limitation, it is noteworthy that Scopus is widely recognized as a suitable database for conducting bibliometric analyses and systematic reviews [50]. Additionally, the set of keywords used to retrieve documents in the field of EF may not be exhaustive. Given the inherent challenge of identifying all relevant documents in this field, we recognize the need for a more comprehensive set of keywords. The incorporation of logical operators in the search strategy also enhances the precision of the retrieved results. Furthermore, selecting only 51 articles for systematic reviews may be considered modest, and as such, the results obtained may not provide a truly comprehensive assessment of issues related to EFs. A broader selection of articles in future reviews would contribute to a more thorough understanding of the subject matter. Despite these limitations, we believe that the findings of this study make a meaningful contribution to the existing body of knowledge in the field of EFs.

In conclusion, our PRISMA-guided dual approach to bibliometric analysis and systematic review has provided a holistic view of EF research. The identified trends, clusters, and insights contribute to the collective knowledge of the field, guiding researchers, practitioners, and policymakers in shaping the future of EFSs. As the landscape continues to evolve, our study stands as a foundational resource for those navigating the intricacies of EF research, offering a roadmap for future investigations.

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