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Knowledge Extraction as an Emerging Discipline: A Bibliographic Analysis

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ABSTRACT

This study aims to conduct a bibliometric analysis on knowledge extraction to examine its grassroots and interdisciplinary interactions based on papers in the Scopus database between 1980 and 2022. The study uses Biblimetrix, performance analysis, and science mapping techniques using 307 papers extracted from the Scopus database. The study used Biblimetrix (R package) and VOSviewer as a tool to carry out the performance analysis and science mapping analysis. The results show that the number of publications has significantly increased in the past decade, 1.53% of authors contribute at least a single article, and 98.46% of authors published multi-authored. China, the USA, and Japan were the most prolific countries in terms of the total number of citations and foreign collaborations. Expert Systems with Applications and the Journal of Knowledge Management are the top journals for knowledge extraction; Advances in Intelligent Systems and Computing (book series), and Lecture Notes in Computer Science are the top conference proceedings series in this field. Implications of the knowledge extraction as an emerging discipline have been discussed based on the evidence and trends. The bibliometrics analysis can be useful for professionals, scholars, and academics interested in bibliometric studies. it also provides the essential information for making decisions on the vitality of disciplines.

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1. Introduction

The general characteristics of a discipline and the various uses of different disciplines facilitate the knowledge distribution and the organization of that discipline (D'Agostino, 2012). In each discipline, there is an unbalanced and highly specialized network that is ready to emerge as a discipline whose probability of emergence depends on the location of emerging leaders in that network and the efficiency of communication between network nodes. The success of this network depends on managing and monitoring the repetition of node performance at different times and different levels (Barnard, 2006). As an academic discipline based on the new paradigm of information technology (Enemark, 2002), Knowledge management also needs to be re-engineered.

Knowledge management (KM) has been applied as a necessary process in organizations and has undergone many changes since the advancement of technology. KM as an interdisciplinary field of study (Oskouei, 2013) consists of a combination of several processes, each of which is specific and unique in achieving the desired knowledge. Knowledge management is the identification, acquisition, extraction, organization, storage, and transfer of appropriate knowledge in order to improve the perception and performance of staff at various levels of the organization at the right time (Nonaka, 2009). Hence, Knowledge acquisition is necessary to enable new Knowledge in the organization (Annosi et al., 2021). Knowledge extraction is the main and initial part of the knowledge acquisition process, which is followed by the transfer of expertise from the knowledge source (Dalkir, 2005), and belongs to the first stage of Dakir's knowledge management process (2013).

Knowledge extraction (KE) in a KM process is in the second phase after the identification and analysis of knowledge in knowledge acquisition process. KE is such important that without it, it will not be possible to create a process and evaluate knowledge in the organization (Nonaka, 2009; Matos & Chalmeta, 2007). Moreover, it is one of the important aspects of knowledge discovery in databases to ensure that correct and impressive knowledge is extracted and available to stakeholders and decision-makers (Nohuddin et al., 2018). KE is also defined as the second phase of Lin and Tserng's (2004) knowledge management life cycle. on the other hand, knowledge extraction is a very complicated task (Chergui, 2020) that needs more attention to make the knowledge management process more useful and proper.

knowledge extraction is described as knowledge creation from data sources, which can be structured (e.g. relational databases, object-oriented database models, UML, XML, and their fuzzy extensions), semi-structured (e.g. infoboxes), and unstructured (e.g. text, documents, images) data sources. In knowledge extraction, a machine-processable format is required for inference. The extracted knowledge is utilized to create or enrich a domain ontology (Terletskyi, 2017; Jiomekong & Camara, 2018), which is a fundamental fact in the knowledge extraction process. Using built ontologies, concepts of domain, context, and data can be used to represent and store knowledge (Jiomekong & Camara, 2018).

In other words, knowledge extraction is the process of converting data and information into knowledge (Tserng & Lin, 2004). Knowledge extraction helps to discover some valuable and potential information from the data that can lead to better decisions (Akbar et al., 2020).

Given the importance of the knowledge extraction in the KM process, and to articulate its emerging process, we intended to study the related scientific literature. Therefore, the bibliometric analysis used in previous KM studies (Gaviria-Marin et al., 2019; Sanguankaew & Ractham, 2019; Schiuma et al., 2020; Farooq, 2021; Thomas & Gupta, 2021) is likewise used in this study. The bibliometric analysis combines a variety of frameworks and methods to study and analyze scientific journals, the results of which develop criteria for gaining new insights and creating new thought structures, discovering emerging trends in articles, the most productive authors, and collaboration patterns about an academic discipline. (Akhavan et al., 2016). Therefore, the results of this study can bring a new insight on KE to KM programs for professionals, knowledge managers, and experts.

In this paper, we propose the emergence of an interdisciplinary called the knowledge extraction approach within knowledge management by knowledge acquired from our bibliometrics study.

The study endeavors to answer the following questions to discover the possibility of forming a research discipline into KM literature as KE based on available capabilities:

Q1. How is the publication trend of papers in KE?

Q2. Who are the most cited authors and documents?

Q3. What are the core knowledge management journals?

Q4. Which are the widely cited countries and affiliations?

Q5. What are the frequently used KE themes?

Q5. What are the most prolific author, document, country, affiliation, and journal in the area of knowledge extraction in knowledge management research?

2. Method

There are a variety of literature review methods such as qualitative analyses or meta-analyses (Castagna et al., 2020; Liberati et al., 2009; Melo et al., 2020; Wadesango et al., 2020) in the research world that aim to systematize a particular search through steps (Moher, 2009). Bibliometric approaches are also in the group of literature review methodologies (Centobelli et al., 2021). The bibliometric analysis is used to measure, analyze, and summarize the available literature on knowledge extraction and knowledge management. The bibliometric analysis has been used by researchers in various fields (Jalal, 2019; Niknejad et al, 2021; Chaudhuri et al., 2021; Gaviria-Marin et al., 2018). The bibliometric analysis retrospects and delineates and reports relationships of research variables using a systematic, clear, and coherent review process (Chen & Xiao, 2016; Perannagari & Chakrabarti, 2020). Alan Pritcard first coined the term Bibliometrics in 1969. This method has a wide range of applications in the field of information science and library (Nayak et al., 2021).

In the present study, an extensive and comprehensive search query was developed by the authors to retrieve all potential documents focusing on knowledge extraction and knowledge management.

Scopus has been used in this research as it is designed for bibliographic research and citation analysis, and it is a suitable alternative to the Web of Science (Vieira and Gomes, 2009; Gaviria-Marin et al., 2019; Farooq, 2022), and it also provides more articles for citation analysis (Falagas et al., 2008, p. 242).

Hence, the study uses Scopus to extract the metadata related to knowledge extraction and knowledge management research. The keywords such as “Knowledge management,” “knowledge extraction” and “knowledge extract*” were used to extract the data from the Scopus. The search was conducted within the article, title, and keywords. Boolean operators such as "AND" and "OR" were used to combine keywords in a search to focus the search on the results that will be most useful. TITLE-ABS-KEY ("knowledge extraction") AND ("knowledge management"). The query for the search was performed as follows and 307 records were retrieved:

(TITLE-ABS-KEY ("knowledge extraction") AND TITLE-ABS-KEY ("knowledge management")) AND PUBYEAR > 1980

The filter was used, and the search was limited to published year, and language. The search was conducted in March 2022, and studies published between 1980 and the present time in 2022 were taken into consideration. It is worth mentioning that the study under consideration has 219 documents in the field of computer science representing 71.33% of the overall results. Other domains publish in the field of knowledge extraction and knowledge management, including Engineering (with 101 documents, representing 32.89% of the overall results), Mathematics (with 51 documents, representing 16.61%), Decision Sciences (with 48 documents, representing 15.63), Business, Management and Accounting (with 44 documents, representing 14.33 %), Social Sciences (with 23 documents, representing 7.49 %), Medicine (with 13 documents, representing 4.23 %), Materials Science (with 7 documents, representing 2.28%), Physics and Astronomy (with 6 documents, representing 1.95%), Energy (with 5 documents, representing 2.25%).

3. Findings

Data analysis

For the data analysis and visualization, bibliometrix (R package) and VOSviewer are applied to perform bibliometric analysis on the search results consisting of 307 records from Scopus. Bibliometrix is based on R (an open-source statistical language) and is designed to assist researchers in conducting automated science mapping (Aria & Cuccurullo, 2017; Quoted in Perannagari & Chakrabarti, 2020; Van Eck & Waltman, 2010).

The bibliometrics study will suggest a general perspective of a field; furthermore, previous studies indicated that this approach has been applied to the LIS field. VOS viewer software visualizes bibliographic information of scientific publications through the indicators of bibliometrics (Saberi et al., 2019).

Performance analysis

Annual total citations per year

An article on KE in KM had not been published from 1980 to 1998. The year 2000 had 1 article published in KE in KM with 19 citations per article, and the average number of citations per year was 22. The years 1998 (1 article) to 2005 (5 articles) were the least productive in terms of the number of papers published; however, the average number of citations has significantly improved from 0 (average citations per article) in 1999 to 23.5 (average citations per article) in 2003. Accordingly, the highest average number of citations per article relates to 4 articles in 2003 with 23.5; and the highest average number of citations per year relates to 17 articles in 2017 with 3.49. It is worth noting that the years 2019 and 2020 equally (with 28 articles) were most productive with regard to the number of articles published.

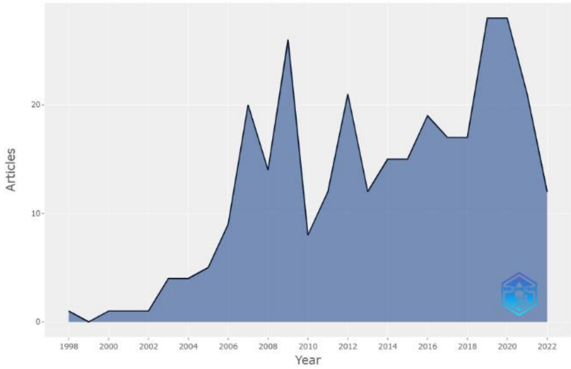


Figure 1. Annual scientific production (1998–2022)

Publication trend

The publication trend of articles was calculated from 1980 to 2022, as shown in Table 1. The 307 articles were published from 1998 to 2022 in KE in KM with 8.27 average years from publication. The average number of citations per document was 7.86, with 0.89 average citations per document per year. Out of 307 documents, 92 articles, 194 conference papers, 11 conference reviews, 6 reviews, 2 books, and 2 book chapters were published in the knowledge extraction and KM research. The results indicate 915 authors with 823 author keywords, including 14 single-authored and 901 multiple-authored documents. The collaboration index measures the level of collaboration practices between the authors, and the results indicate 3.2 authors per document in the KE in KM research.

Table 1. Scientific production from 1980 to 2022

Results	**Description (MAIN INFORMATION ABOUT DATA)**	**Results**	**Description (MAIN INFORMATION ABOUT DATA)**
	DOCUMENT CONTENTS	1998:2022	Timespan
2197	Keywords Plus (ID)	200	Sources (Journals, Books, etc)
823	Author's Keywords (DE)	307	Documents

	AUTHORS	8.27	Average years from publication
915	Authors	7.86	Average citations per documents
1030	Author Appearances	0.8946	Average citations per year per doc
14	Authors of single-authored documents	8318	References
901	Authors of multi-authored documents		DOCUMENT TYPES
	AUTHORS COLLABORATION	92	article
25	Single-authored documents	2	book
0.336	Documents per Author	2	book chapter
2.98	Authors per Document	194	conference paper
3.36	Co-Authors per Documents	11	conference review
3.2	Collaboration Index	6	review

Analysis of the most productive authors

The scientific production of authors was calculated by the number of articles contributed by each author, as shown in Figure 2. The scientific output of top 20 authors was determined by the bubble size, color intensity, and the author's timeline. The bubble size is proportional to the number of documents, and the line indicates an author's timeline. Figure 2 indicates that Hou (2.17) was the most productive author in terms of the frequency of publications from 2006 to 2013, as indicated by the color intensity. However, the author(s) with maximum citations include Chakraborty (2.363), Hou (1.621), and Chen (1.237) from 2007 to 2022.

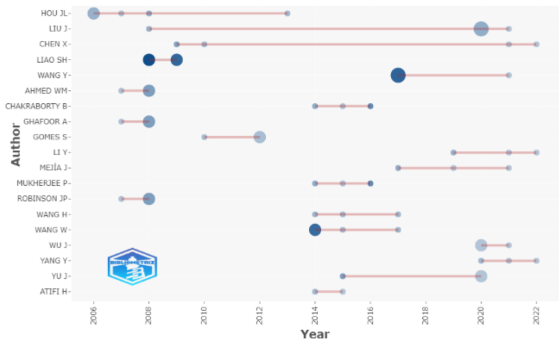


Figure 2. Top-authors' publication over time (1998–2022)

The authors such as Hou and Liu contributed 5 and 4 articles each respectively, as indicated by the thickness of the node. The authors, including Ahmed, Chakraborty, Ghafoor, and Gomes contributed 3 articles from 2007 to 2022. Atifi with 2 and Li with one article contribute with the least number of articles. However, it is worth noting that Ahmed and Ghafoor were the most productive author with regard to the total number of citations received (16), followed by Chen with 13 citations. The color intensity is proportional to the total citations per year. The authors such as Liu and Chen have been the most consistent in terms of the number of citations received per year in KE.

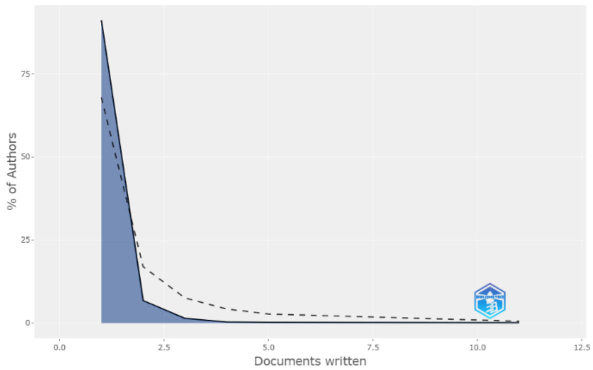


Figure 3. Frequency distribution of scientific productivity (Lotka's law)

The study applies Lotka's law to describe the number of publications by authors in KE in KM. Lotka's law indicates the inverse relationship between the number of articles and the frequency of the authors published a such number of articles (Sun, 2021). The results of Lotka's law indicate that 0.911% of authors contribute one article, 0.068% of authors contribute two articles, 0.014% of the authors published three documents, 0.003% of the authors contribute four documents, and 0.002% of the authors contribute five documents as shown in Figure 3.

Table 2. Authors' production through Lotka's law

Documents written	N. of Authors	Proportion of Authors
1	834	0.911
2	62	0.068
3	13	0.014
4	3	0.003
5	2	0.002
11	1	0.001

Table 2 indicates that 0.001% of the authors published eleven articles in the field of KE.

Analysis of the most cited documents

This section shows the analyses twofold. First, Figure 4 illustrates the most local cited documents, which illustrates the number of citations an article received from the articles included in the analyzed Scopus collection. In this regard, the most cited documents were by Liao (2008), and Hou (2006) with 2 local citations, as shown in figure 4.

Table 3 shows the most local cited documents, in which Younan (2020), Giannoulis (2018), Mejía (2017), Corcoglioniti (2016), Mukherjee (2014), Wijayasekara (2014), Lahoud (2010), Cantú (2010), Nakayama (2007), and Rao (1998) have 1 citation equally.

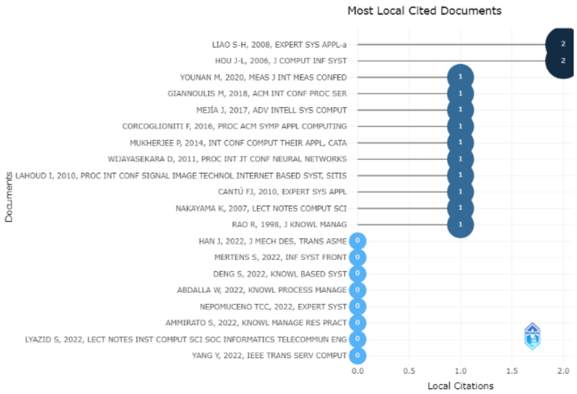


Figure 4. The most local cited documents

Table 3. The most local cited documents

Document	Year	LC/GC Ratio (%)	Global Citations	Local Citations	Normalized Global Citations	Normalized Local Citations
LIAO S-H, 2008, EXPERT SYS APPL-a	2008	4.88	41	2	4.56	15.00
HOU J-L, 2006, J COMPUT INF SYST	2006	22.22	9	2	0.78	8.00
YOUNAN M, 2020, MEAS J INT MEAS CONFED	2020	2.13	47	1	13.90	21.00
GIANNOULIS M, 2018, ACM INT CONF PROC SER	2018	20.00	5	1	1.16	19.00
MEJÍA J, 2017, ADV INTELL SYS COMPUT	2017	25.00	4	1	0.35	19.00
CORCOGLIONITI F, 2016, PROC ACM SYMP APPL COMPUTING	2016	5.00	20	1	3.84	19.00
MUKHERJEE P, 2014, INT CONF COMPUT THEIR APPL, CATA	2014	16.67	6	1	1.15	17.00
WIJAYASEKARA D, 2011, PROC INT JT CONF NEURAL NETWORKS	2011	4.35	23	1	6.10	13.00
LAHOUD I, 2010, PROC INT CONF SIGNAL IMAGE TECHNOL INTERNET BASED SYST, SITIS	2010	33.33	3	1	1.04	4.50
CANTÚ FJ, 2010, EXPERT SYS APPL	2010	9.09	11	1	3.81	4.50
NAKAYAMA K, 2007, LECT NOTES COMPUT SCI	2007	1.54	65	1	6.64	23.00
RAO R, 1998, J KNOWL MANAG	1998	25.00	4	1	1.00	1.00
HAN J, 2022, J MECH DES, TRANS ASME	2022		0	0	0.00	
MERTENS S, 2022, INF SYST FRONT	2022	0.00	2	0	3.67	
DENG S, 2022, KNOWL BASED SYST	2022	0.00	1	0	1.83	
ABDALLA W, 2022, KNOWL PROCESS MANAGE	2022		0	0	0.00	
NEPOMUCENO TCC, 2022, EXPERT SYST	2022		0	0	0.00	
AMMIRATO S, 2022, KNOWL MANAGE RES PRACT	2022		0	0	0.00	
LYAZID S, 2022, LECT NOTES INST COMPUT SCI SOC INFORMATICS TELECOMMUN ENG	2022		0	0	0.00	
YANG Y, 2022, IEEE TRANS SERV COMPUT	2022		0	0	0.00	

Second, Figure 5 depicted the most global cited documents, which shows Handschuh (2002), and Hoffart (2012) are at the top of this list.

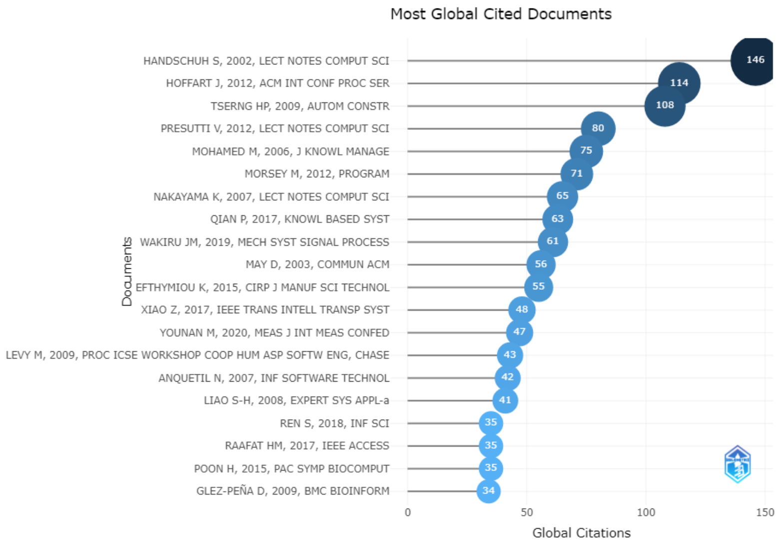


Figure 5. The most global cited documents

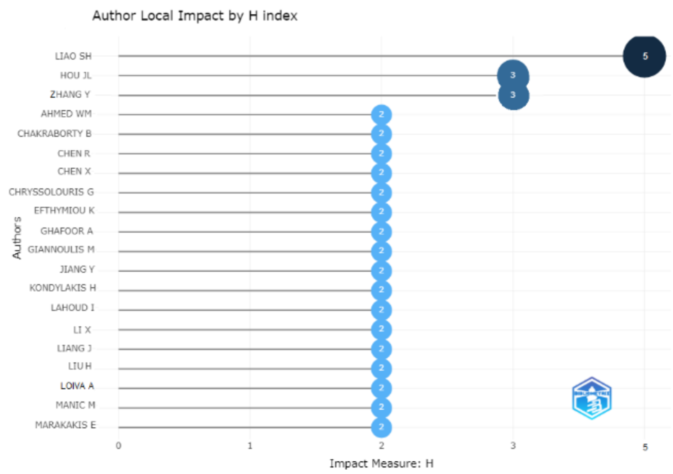


Figure 6. Most prolific authors based on h_index

Table 4. The most global cited documents

Normalized TC	TC per Year	Total Citations	Paper
1.8599	6.9524	146	HANDSCHUH S, 2002, LECT NOTES COMPUT SCI
7.5562	10.3636	114	HOFFART J, 2012, ACM INT CONF PROC SER
6.8693	7.7143	108	TSERNG HP, 2009, AUTOM CONSTR
5.3026	7.2727	80	PRESUTTI V, 2012, LECT NOTES COMPUT SCI
6.5217	4.4118	75	MOHAMED M, 2006, J KNOWL MANAGE
4.7061	6.4545	71	MORSEY M, 2012, PROGRAM
6.6444	4.0625	65	NAKAYAMA K, 2007, LECT NOTES COMPUT SCI
5.4409	10.5	63	QIAN P, 2017, KNOWL BASED SYST
9.3533	15.25	61	WAKIRU JM, 2019, MECH SYST SIGNAL PROCESS
3.9298	2.8	56	MAY D, 2003, COMMUN ACM
5.7716	6.875	55	EFTHYMIOU K, 2015, CIRP J MANUF SCI TECHNOL
4.1455	8	48	XIAO Z, 2017, IEEE TRANS INTELL TRANSP SYST
13.9014	15.6667	47	YOUNAN M, 2020, MEAS J INT MEAS CONFED
2.735	3.0714	43	LEVY M, 2009, PROC ICSE WORKSHOP COOP HUM ASP SOFTW ENG, CHASE

4.2933	2.625	42	ANQUETIL N, 2007, INF SOFTWARE TECHNOL
4.5556	2.7333	41	LIAO S-H, 2008, EXPERT SYS APPL-a
8.1098	7	35	REN S, 2018, INF SCI
3.0227	5.8333	35	RAAFAT HM, 2017, IEEE ACCESS
3.6728	4.375	35	POON H, 2015, PAC SYMP BIOCOMPUT
2.1625	2.4286	34	GLEZ-PEÑA D, 2009, BMC BIOINFORM

On the other hand, their comparison shows that Nakayama (2007), Younan (2020), and Lia (2008) with 65, 47, and 41 global citations, respectively, have overlap among the top 20 authors in the list of the most global cited documents and local ones, as shown in Table 4.

Authors' h-index

The study analyzes the h-index of KE in KM studies to measure the productivity and citation impact of publications of authors. Liao was the most productive with four h-index followed by Hou with a 3-h index each, as shown in Figure 6. The rest of the authors are most consistent with the 2-h index indicating that two documents were cited at least two times in the KE and KM studies.

Analysis of most local cited sources

The most local cited sources are listed in Figure7. This shows sources such as journals or conference proceedings that were included in at least one of the reference lists of the article set from 1998-to 2022. The most cited journals are Journal of Expert Systems with Applications with 57 citations, and Journal of Knowledge Management with 55 citations. Following these two most cited journals, Automation in Construction, and IEEE Transactions on Knowledge and Data Engineering are the third and fourth, respectively, most cited sources.

Source dynamics and Bradford's distribution

Source dynamics describes the annual occurrences of the terms (Farooq, 2022) KE and KM in various journals. The Lecture Notes in Computer Science with 219 was the most productive in terms of the frequency of the publications from 2002 to 2022, as shown in Table 5.

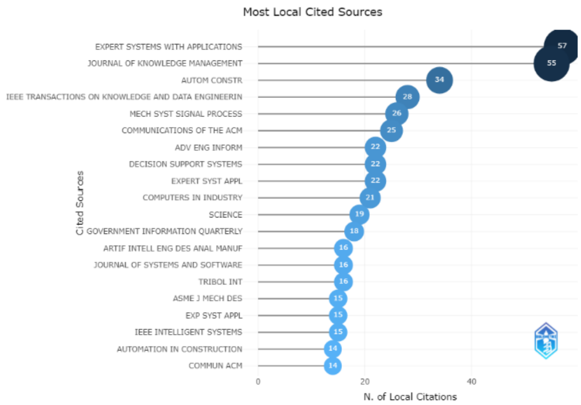


Figure 7. The most local cited sources

International Conference on Information and Knowledge Management, Proceedings, with 105 and Expert Systems with Applications with 85 are at the second and third rank.

Table 5. Source dynamics (1998–2022)

COMMUNICATIONS IN COMPUTER AND INFORMATION SCIENCE	CEUR WORKSHOP PROCEEDINGS	EXPERT SYSTEMS WITH APPLICATIONS	INTERNATIONAL CONFERENCE ON INFORMATION AND KNOWLEDGE MANAGEMEN, PROCEEDINGS	ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES	LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS)	Year
0	0	0	0	0	0	1998
0	0	0	0	0	0	1999
0	0	0	0	0	0	2000
0	0	0	0	0	0	2001
0	0	0	0	0	1	2002
0	0	0	0	0	1	2003
0	0	0	1	0	1	2004

0	1	0	1	0	1	2005
0	1	0	1	0	1	2006
0	1	0	1	0	4	2007
0	1	2	2	0	7	2008
0	1	3	4	0	7	2009
0	1	4	4	0	8	2010
1	1	4	6	0	9	2011
2	1	5	6	4	11	2012
4	2	5	6	4	11	2013
4	3	6	6	4	13	2014
4	3	6	6	5	13	2015
4	4	6	6	6	14	2016
4	5	6	7	6	15	2017
5	5	6	8	8	17	2018
5	6	8	8	10	20	2019
7	6	8	10	10	21	2020
7	7	8	11	11	22	2021
7	7	8	11	11	22	2022

We applied Bradford's law to describe the distribution of titles in a certain area in journals. This law focuses on central productivity areas and shows that efficiency decreases with publishing comprehensive literature. Journals are divided into different zones based on the number of articles (Singh et al., 2016). Bradford's law of scattering indicates that the Lecture Notes in Computer Science as the first, and the ACM International Conference on Information and Knowledge Management, Proceedings equally as the second rank are the core sources of knowledge extraction and KM studies, as shown in Figure 8.

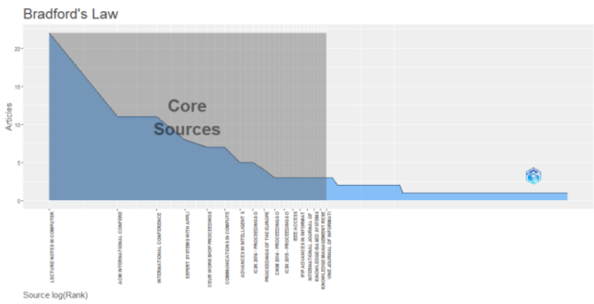


Figure 8. Distribution of titles based on Bradford's law

Table 6. Bradford's distribution of titles

Zone	Cum. Freq	Freq	Rank	SO
Zone 1	22	22	1	LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS)
Zone 1	33	11	2	ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES
Zone 1	44	11	3	INTERNATIONAL CONFERENCE ON INFORMATION AND KNOWLEDGE MANAGEMENT, PROCEEDINGS
Zone 1	52	8	4	EXPERT SYSTEMS WITH APPLICATIONS
Zone 1	59	7	5	CEUR WORKSHOP PROCEEDINGS
Zone 1	66	7	6	COMMUNICATIONS IN COMPUTER AND INFORMATION SCIENCE
Zone 1	71	5	7	ADVANCES IN INTELLIGENT SYSTEMS AND COMPUTING
Zone 1	76	5	8	IC3K 2016 - PROCEEDINGS OF THE 8TH INTERNATIONAL JOINT CONFERENCE ON KNOWLEDGE DISCOVERY, KNOWLEDGE ENGINEERING AND KNOWLEDGE MANAGEMENT
Zone 1	80	4	9	PROCEEDINGS OF THE EUROPEAN CONFERENCE ON KNOWLEDGE MANAGEMENT, ECKM
Zone 1	83	3	10	CIKM 2014 - PROCEEDINGS OF THE 2014 ACM INTERNATIONAL CONFERENCE ON INFORMATION AND KNOWLEDGE MANAGEMENT
Zone 1	86	3	11	IC3K 2019 - PROCEEDINGS OF THE 11TH INTERNATIONAL JOINT CONFERENCE ON KNOWLEDGE DISCOVERY, KNOWLEDGE ENGINEERING

				AND KNOWLEDGE MANAGEMENT
Zone 1	89	3	12	IEEE ACCESS
Zone 1	92	3	13	IFIP ADVANCES IN INFORMATION AND COMMUNICATION TECHNOLOGY
Zone 1	95	3	14	INTERNATIONAL JOURNAL OF KNOWLEDGE MANAGEMENT
Zone 1	98	3	15	KNOWLEDGE-BASED SYSTEMS
Zone 1	101	3	16	KNOWLEDGE MANAGEMENT RESEARCH AND PRACTICE
Zone 1	104	3	17	VINE JOURNAL OF INFORMATION AND KNOWLEDGE MANAGEMENT SYSTEMS
Zone 2	107	3	18	YEARBOOK OF MEDICAL INFORMATICS
Zone 2	109	2	19	55TH ANNUAL MEETING OF THE INTERNATIONAL SOCIETY FOR THE SYSTEMS SCIENCES 2011
Zone 2	111	2	20	8TH INTERNATIONAL CONFERENCE ON MACHINE LEARNING AND APPLICATIONS, ICMLA 2009

The law identifies two zones, with Zone 1 having 17 journals, followed by Zone 2 with 3 journals, as shown in Table 6. Bradford's law of scattering predicts the increasing productivity of journals from one zone to the next zone (Bradford, 1985; Swain, 2013).

The distribution of articles and journals according to Bradford's predicted zones is as follows:

Zone I. 17 journals and 104 articles;

Zone II. 3 journals and 101 articles.

Most cited countries

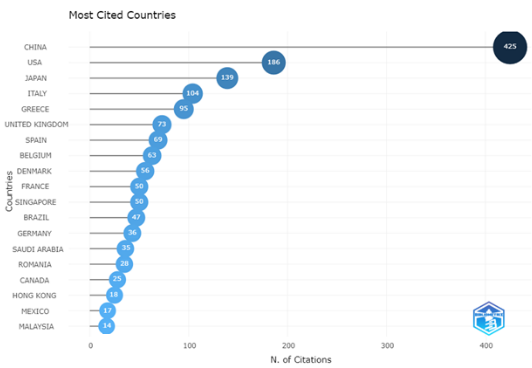


Figure 9. Most cited countries

The results indicate that the China was the most cited country with 425 citations and 9.66 average article citations, as shown in Figure 9. The USA contributed 186 citations with 8.86, Japan 139 citations with 15.44, Italy 104 citations with 14.86, and Greece 95 citations with 19 average article citations from 1998 to 2022. However, Denmark was most productive with regard to the average article citations with 56, as shown in Table 7. The top ten countries contributed more than 1500 citations, and the rest of the countries contributed less than 100 citations. China was most productive in Asia, followed by Japan and Singapore with 425, 139, and 50 citations.

The countries, including Australia, Iran, Korea, Switzerland, Nigeria, Poland, Portugal, Latvia, Panama, Austria, Pakistan, Thailand, Ukraine were the least productive with less than 10 citations; therefore, the journals such as Journal of Knowledge Management, Journal of Knowledge Management Research and Practice, and other journals should promote KE in KM research in these countries.

Most relevant affiliations

Universities have been the most consistent platforms to promote and support research. Tsing Hua University was the most productive in terms of the frequency of publications, followed by Tam Kang University, as shown in Figure 10. Fudan University, Iowa State University, National Tsing Hua University, Purdue University, Université de Lyon, University of Science and Technology Beijing, University of Sheffield contributed 4 articles; Centro de Investigación en Matemáticas, Federal University of Pernambuco, Federal University of Rio de Janeiro- UFRJ, King Saud University, Loughborough University, National Taiwan University, Peking University, Shenzen University, the University of Calgary contributing three articles from 1998 to 2022. However, the institutions such as the Institute of Cytology and Genetics, the National Institute of Technology published 4 and 3 documents, respectively, as shown in Figure 10. It is important to note that majority of the research is dominated by China.

Table 7. Most cited countries

Country	Total Citations	Average Article Citations
CHINA	425	9.66
USA	186	8.86
JAPAN	139	15.44
ITALY	104	14.86
GREECE	95	19.00
UNITED KINGDOM	73	8.11
SPAIN	69	9.86
BELGIUM	63	31.50
DENMARK	56	56.00
FRANCE	50	4.17
SINGAPORE	50	25.00
BRAZIL	47	7.83
GERMANY	36	3.60
SAUDI ARABIA	35	17.50
ROMANIA	28	14.00
CANADA	25	8.33
HONG KONG	18	18.00
MEXICO	17	4.25
MALAYSIA	14	7.00

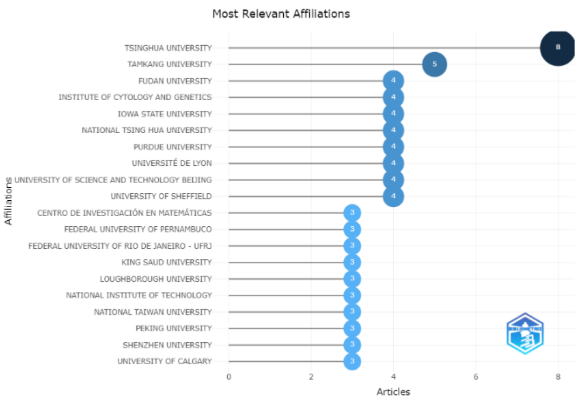
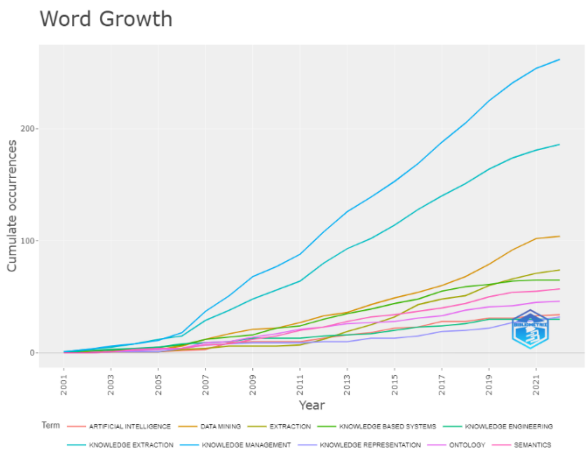


Figure 10. Most relevant affiliations

Analysis of keywords

To intuitively show the evolution of keywords over time from 1980 to March 2022, we draw a word growth graph using Bibliometrix, as shown in Fig. 11. It can be seen that knowledge management has always been a hot topic, and knowledge extraction has been attracting increasing attention since 2001. In addition, in recent years, keywords such as data mining, knowledge-based systems, and extraction have been discussed frequently and become hot topics. It can be seen that all keywords have been increasing during the time.

Figure 11. Word growth (1980-2022)



The results of the bibliometrix indicate that knowledge management was the frequently used keyword with 262 occurrences, followed by knowledge extraction with 186 occurrences, as shown in Figure 11. The study used frequency as the word occurrence measure to identify the frequently used keywords in KE in knowledge management. The keywords, including extraction, artificial intelligence, and knowledge representation have been used 74, 34, and 32 times from 1980 to 2022. The other widely used keywords in the KE in knowledge management research include data mining, knowledge-based systems, semantics, ontology, and knowledge engineering with 104, 65, 57, 46, and 30 occurrences, respectively.

The results of the treemap suggest that knowledge management constitutes 18% of the total keywords, followed by knowledge extraction 13%, data mining 7 %, extraction 5%, knowledge-based systems, and semantics 4%, and ontology 3% as shown in Figure 12.

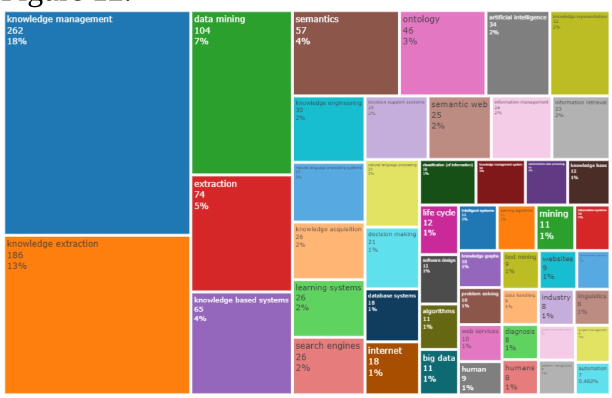


Figure 12. Treemap of keywords in the knowledge management (1988–2022)

Science mapping analysis

Co-occurrence of keywords

Keywords are used as a practical tool in identifying research content, core topics, and methods used in any particular research (Huang et al., 2020). The frequency of a keyword is known as occurrence. On the other hand, the frequency of simultaneous occurrence of a keyword pair is called co-occurrence. Therefore, by determining the keyword co-occurrence, the hot spots of the research field can be identified (Deveci, 2021). The relationship between the keywords in the form of a network map is displayed by a keyword co-occurrence network (Huang et al., 2020).

The results of the co-occurrence network indicate several keywords such as knowledge management, knowledge extraction, data mining, knowledge-based systems, extraction, semantics, and ontology; however, knowledge management is at the center of the network as indicated by the vertex size. Each vertex in the network represents an item or a keyword, and vertex size is proportional to the item occurrence. The edge size represents the strength of the relationship between the keywords. The width of the line between two keywords indicates the citation relationship between keywords. The thickness of the lines between nodes indicates the number of co-occurrences between the two authors–keywords (Yu et al., 2020).

The thickness of the edge shows that knowledge management was widely studied with knowledge extraction, extraction, data mining, knowledge representation, semantics, and ontology, as shown in Figure 13.

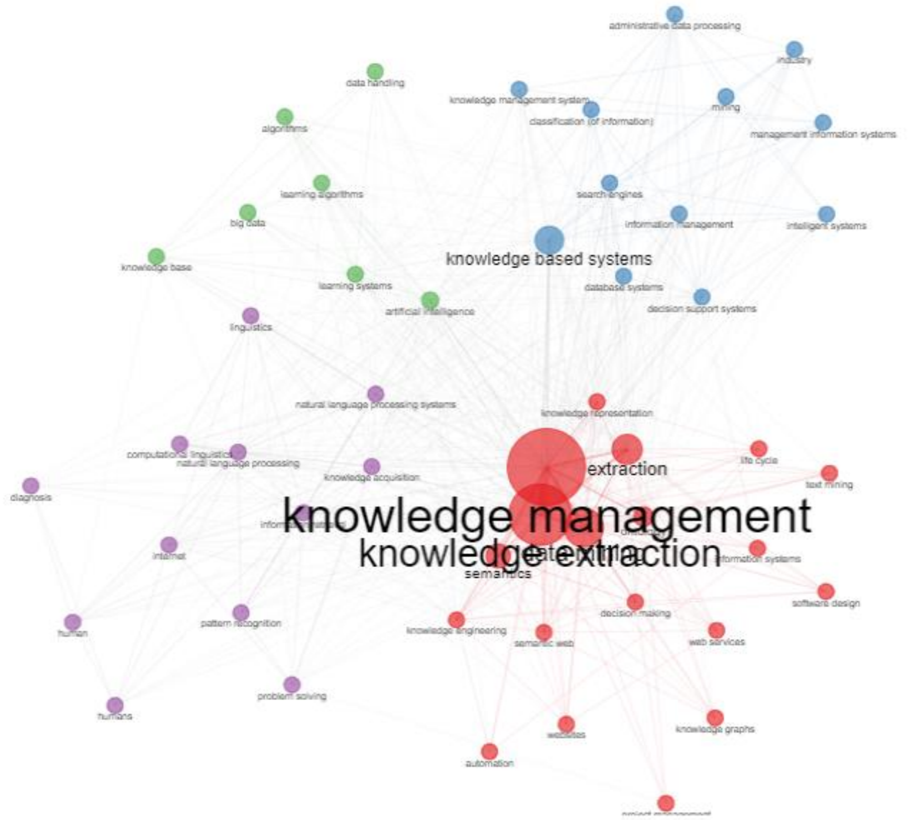


Figure 13. Co-occurrence of keywords

The study uses betweenness centrality and closeness centrality as the measures of the occurrence of keywords. The centrality indicators are calculated using the relationship between the nodes in a scientific collaboration network (Gholampour et al., 2019). The keywords such as knowledge management, knowledge extraction, and data mining, which belong to cluster 1, have the most betweenness centrality. In other words, these keywords are located within the shortest distance among other keywords. However, in Cluster 2, knowledge-based systems have the highest betweenness centrality, followed by search engines, and decision support systems. Artificial intelligence, learning systems, and knowledge base in cluster 3, and natural language processing systems, knowledge acquisition, information retrieval in cluster 4 have the highest betweenness among other keywords, as shown in Table 8.

Table 8. Ranking of top keywords based on centrality measures

Node	Cluster	Betweenness	Closeness	PageRank
knowledge management	1	395.0143517	0.020408163	0.1424137
knowledge extraction	1	171.3697838	0.020408163	0.106314087
data mining	1	41.91233322	0.018181818	0.062112806
knowledge based systems	2	20.97873511	0.016666667	0.045052654
search engines	2	3.766383677	0.014492754	0.021665142
decision support systems	2	4.721482562	0.014084507	0.021778274
artificial intelligence	3	11.17231518	0.016393443	0.028506308
learning systems	3	3.707703734	0.014285714	0.021989243
knowledge base	3	0.314878484	0.012195122	0.010268456
natural language processing systems	4	5.022276787	0.014492754	0.024075677
knowledge acquisition	4	3.085913978	0.014084507	0.019442549
information retrieval	4	2.614505626	0.013513514	0.01861246

On the other hand, artificial intelligence in Cluster 3, and natural language processing systems in cluster 4 have the highest betweenness centrality; knowledge management, knowledge extraction, data mining, and extraction 1 have the highest closeness centrality in Cluster 1, followed by knowledge-based systems in Cluster 2, artificial intelligence in cluster 3, semantics and ontology in cluster 1, search engines in cluster 2, and natural language processing systems in cluster 4.

All these keywords have the most closeness to other keywords in the network, which indicates that these keywords are closely studied in relation to each other.

Studies in the past have widely discussed knowledge management with knowledge extraction (Silwattananusarn & Tuamsuk, 2012; Levy & Hazzan, 2009; Anquetil et al., 2007), data mining (Silwattananusarn & Tuamsuk, 2012; Mohd Selamat et al., 2020; Zhan et al., 2019), and knowledge-based systems (Butt et al., 2019; Szczerbicki & Sanin, 2020), extraction (Mohamed et al., 2020; Sahay et al., 2021; Fan & Wang, 2022), artificial intelligence (de Carvalho Botega & da Silva, 2020, Wang & Wu, 2021).

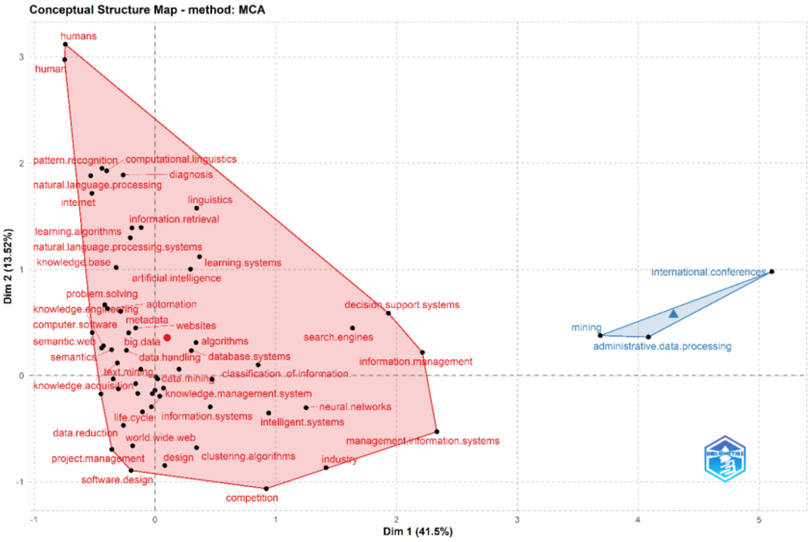


Figure 14. The Multiple Correspondence Analysis (MCA) of the keywords

The Multiple Correspondence Analysis (MCA) of the keywords included in our bibliographic dataset was conducted. The analysis draws a conceptual structure of the field and K-means clustering to identify clusters of documents that express common concepts (Aria & Cuccurullo, 2017).

The figure 14 demonstrates that the published documents under our analysis can be organized into four primary clusters representing the intellectual structure of related studies. Details of each cluster are beyond the scope of the present study. Nevertheless, we show the intellectual focus of research based on proximity or clustering. The most extensive research cluster is highlighted in red in the conceptual structure map. Such a large cluster indicates that most of the research is closely associated with each other to different degrees. A total of 50 keywords are associated with the red cluster, which covers knowledge management, knowledge-based systems, artificial intelligence, and natural language processing systems. Furthermore, the associated studies focus on knowledge management, knowledge extraction, and data mining to a significant extent. On the knowledge management part, we can notice research concentration on the competition, industry, project management, and knowledge acquisition. We do not find any distinctive presence of countries or regions by analyzing the research cluster. Besides, the research has provided a particular focus on the search engines, classification of information, algorithms, and neural networks with the same keywords. Moreover, some studies have concentrated on information retrieval, linguistics, learning algorithms, and knowledge bases; which shows the researchers' interest in artificial intelligence and programming in the field of KM.

Although we notice the close association of research related to mining and data processing in international conferences. Specifically, the publications in international conferences examine the linkages between 'mining' and 'administrative data processing' (Huang et al., 2021; Rassamee & Woradit, 2019).

Coupling map analysis

The coupling map analysis is performed on three units of documents, authors, and sources (Farooq, 2021). In this study, this analysis has been carried out for the "authors". If at least one source is referenced in the bibliography of two articles, the two articles are bibliographically coupled (Aria and Cuccurullo, 2017; Kessler, 1963).

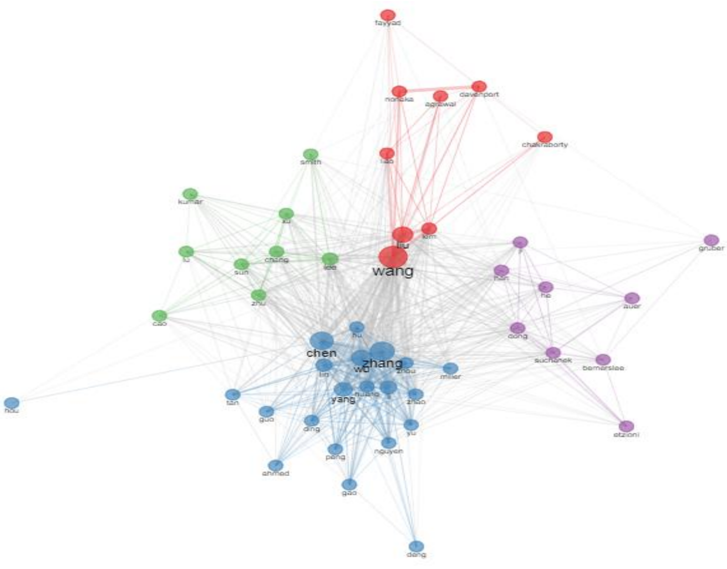


Figure 15. Bibliographic coupling of authors

Figure 15 represents the bibliographic coupling of authors, and the number of citations of each document is indicated by the node size. The degree of node/article relevance is bibliographically indicated by the distance or proximity of studies on the network (Niknejad et al., 2021). Table 9 shows top five clusters with minimum cluster strength of 3. As shown, Li, Chen, Giannoulis are authors with most cluster frequency.

Table 9. Coupling map of authors based on cluster frequency

Impact	Cluster Frequency	Authors	Cluster
1	14	LI Y	8
1	11	CHEN X	3
1	7	GIANNOULIS M	2
1	4	GOMES S	7
1	3	WANG Y	5

Thematic mapping

Thematic mapping of keywords shows the keywords of research topics, key phrases, and the relationships between them (Akter et al., 2021); It also creates a network of word occurrence analysis that reflects key themes and patterns defined in science (Jain et al., 2021). The literature of a field is summarized in typologies of themes that are necessary to determine the thematic status of the field under study (Caust and Vecco, 2017; Jain et al., 2021). One of the recognizable advantages of thematic mapping is that it differentiates the focus of research into different categories based on level. The centrality of a theme is the degree of relation between different topics, and the density indicates the progress of a particular theme (Esfahani et al., 2019). By identifying the authors' keywords, the most relevant topics are plotted on a two-dimensional thematic map. This map shows the power of density and centrality, or in other words, internal and external associations (Breyas & Alon, 2021).

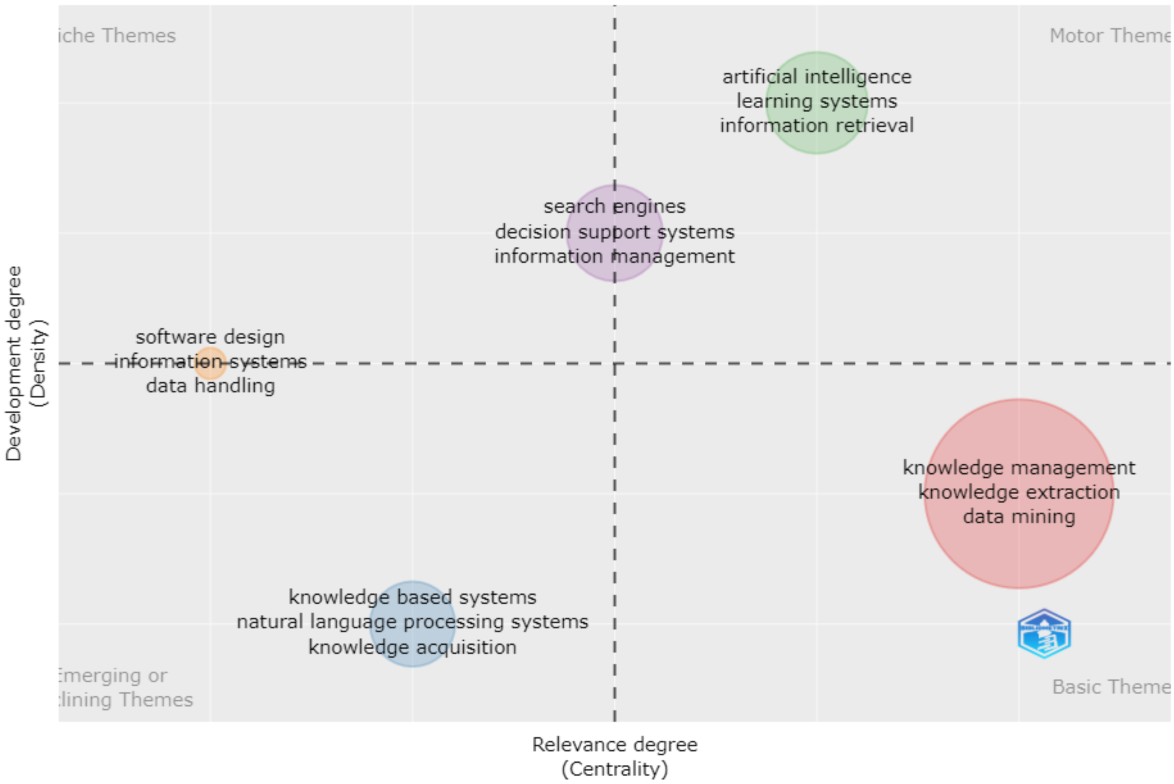


Figure 16. Thematic mapping of studies (1998-2022)

As can be seen in figure 16, it has four quadrants:

1. On the upper right side, we have themes with high density and centrality, which shows the motor themes as the driving force of the research field (Macaskill et al., 2021). Artificial intelligence, learning systems, and information retrieval in the theme of artificial intelligence are mainstream, essential, and developed themes;

2. On the upper left side, we have themes with high density and low centrality, which shows the niche themes; Niche themes are very specialized and well-developed themes of a research area (Cai & Guo, 2021). As it can be seen, there is no well-developed theme in the field of this research.

3. On the lower right side, we have themes with low density and high centrality, which shows the basic themes; Basic themes are important for a research field but not yet well

developed (Yildirim et al., 2022). knowledge management, knowledge extraction, and data mining are the basic themes in this field.

4. On the lower left side, we have themes with low density and centrality, which shows the emerging and declining themes. These themes are weakly developed and marginal (Yildirim et al., 2022). in this theme Knowledge-based systems, natural language processing systems, and knowledge acquisition are the top areas in this theme.

Collaboration network of authors and countries

The collaboration of authors and countries in the field of knowledge extraction in knowledge management was examined. The collaboration network of authors represents the strength of the connection between authors. it depicts the collaboration between an author and other authors in a dataset. Two authors collaborate when they are both listed as authors in the same Scopus document. The link between the authors indicates that there is a thematic connection and commonality between the two authors and the colors used are closer to each other. The larger the node, the more important the author is to the subject. Each cluster represents the authors' collaboration in the field under study (Khazaneha, 2019). Ahmed, Ghafoor, and Robinson are important authors in collaboration in this field, as shown in Table 10.

Table 10. Collaboration network of authors

PageRank	Closeness	Betweenness	Cluster	Node
0.04	0.001811594	0	1	ahmed wm
0.04	0.001811594	0	1	ghafoor a
0.04	0.001811594	0	1	robinson jp
0.04	0.001736111	0	2	chakraborty b
0.04	0.001736111	0	2	mukherjee p
0.04	0.001811594	0	3	gomes s
0.04	0.001811594	0	3	lahoud i
0.04	0.001811594	0	3	monticolo d
0.04	0.001736111	0	4	mejía j
0.04	0.001736111	0	4	muñoz m
0.04	0.001736111	0	5	wang h
0.04	0.001736111	0	5	wang w
0.04	0.001736111	0	6	wu j
0.04	0.001736111	0	6	yu j
0.04	0.001736111	0	7	atifi h
0.04	0.001736111	0	7	matta n
0.04	0.001811594	0	8	chryssolouris g
0.04	0.001811594	0	8	efthymiou k
0.04	0.001811594	0	8	mourtzis d
0.04	0.001811594	0	9	giannoulis m
0.04	0.001811594	0	9	kondylakis h
0.04	0.001811594	0	9	marakakis e
0.04	0.001811594	0	10	hara t
0.04	0.001811594	0	10	nakayama k
0.04	0.001811594	0	10	nishio s

The collaboration network of authors and countries is analyzed on the basis of closeness and betweenness (Borgatti, 2005; Freeman, 1979). Closeness is the shortest path between two nodes, ie two authors in a network (Ashrafi *et al.*, 2020; Fernández *et al.*, 2021; Lu and Feng, 2009); and the betweenness shows how often a node is placed in the shortest path between nodes (Gallego-Cuiñas *et al.*, 2020; Leydesdorff, 2007).

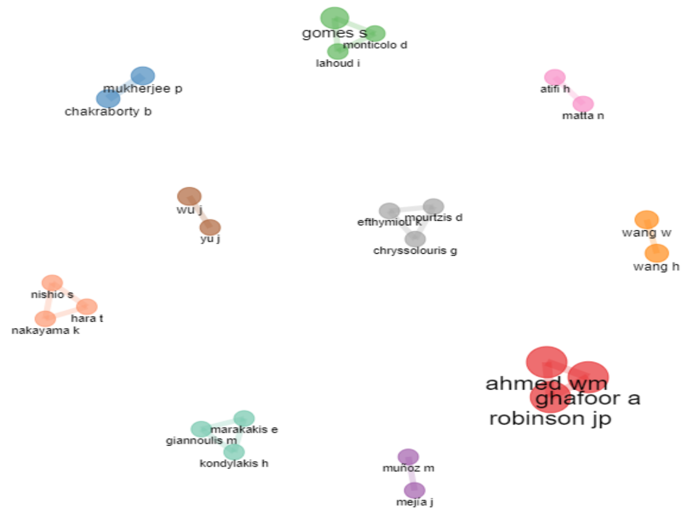


Figure 17. Most collaborative authors (1998–2022)

Figure 17 indicates Ahmed, Ghafoor, and Robinson as the most collaborative authors as indicated by the vertex's size and edge. Table 12 shows that there is no betweenness centrality, which indicates that there is no path between authors in the collaboration network. The authors with the highest closeness centrality include Ahmed, Ghafoor, and Robinson in cluster 1; Gomes, Lahoud, and Monticolo in cluster 3; Chryssolouris, Efthymiou, and Mourtzis in cluster 8; Giannoulis, Kondylakis, and Marakakis in cluster 9; Hara, Nakayama, and Nishio in cluster 10 can reach other authors faster in the collaboration network.

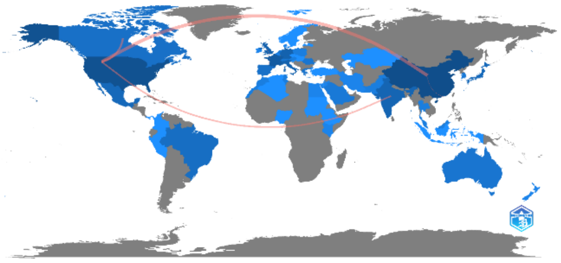


Figure 18. Most collaborative countries in knowledge management (1988– 2021)

The collaboration of each country around the world in the field under study is shown in Figure 18. In this figure, the blue color indicates a country with output, while gray indicates countries without an output. The blue color spectrum reflects the high efficiency of each country. While the red lines indicate the network of collaboration between the countries that have the output (Akter et al., 2021; Farooq, 2022).

Table 11. Most collaborative countries (1988– 2021)

Frequency	From	To
8	CHINA	USA
4	USA	CANADA
3	USA	INDIA
2	CHINA	HONG KONG
2	FRANCE	UNITED KINGDOM
1	AUSTRALIA	DENMARK
1	AUSTRIA	DENMARK
1	BELGIUM	KENYA
1	BRAZIL	PORTUGAL
1	CANADA	MEXICO

The countries that are active in collaboration with other countries include China, the USA, and Canada, as indicated by the red lines in the collaboration map. China to the USA has the highest collaborations with 8, followed by the USA to Canada with 4 and the USA to India with 3, as shown in table 11.

Analysis of findings

To discuss about the capabilities of KE to emerge as a new interdisciplinary, we have provided some reasons using the findings of our research.

Political, economic, environmental, social, and technological issues of societies have become highly vast, complex, and diverse that conducting scientific activities in a single discipline does not have the opportunity to answer and solve a variety of complex issues (Mahdi, 2013). Creating a new discipline of research requires the integration of heterogeneous specialties and resources in one or more fields, which also implies the importance and preservation of the originality of the main discipline (Ávila-Robinson et al., 2014).

Domains are independent and often represent the context of the underlying discipline; As a result, they are easy to generalize and express. But with the emergence of more complex issues, domains need to define and integrate contexts from different disciplines to create the ability to meet the needs of the day. Hence, the goal is to define a new language that can adapt different knowledge in different fields and achieve the appropriate answer. The lack of perceptual structures challenges the possibility of combining knowledge of existing disciplines or technological fields, and creating these structures containing pieces of knowledge unites the previous understanding with the existing spaces in the new problem for more general adaptations. (Nesta, & Dibiaggio, 2002).

Many principles of KM originate from different disciplines with different names, but similar ideologies have emerged that have contributed to the growth of KM (Mehri et al., 2014; Nyamasege, 2019). Various scientometrics studies have been conducted in the field of knowledge management that helped to identify the identity of knowledge management (Kokol et al., 2015; Nyamasege, 2019). We examined the most frequently used words in the papers understudy and show that out of 50 selected keywords, knowledge management with 18.05% and knowledge extraction as the second most repeated keyword with 12.81% have been the most discussed topics among researchers; which is a significant reason in defining interdisciplinary of knowledge management - knowledge extraction. On the other hand, the closeness of keywords in the word co-occurrence network shows a close relationship between knowledge management and knowledge extraction (equal to 0.0204), and also the betweenness shows that the two keywords knowledge management and knowledge extraction are ranked first (395.01) and second (171.36).

Technological knowledge in the global innovation system is at the top of the global value chain (Zhang & Gallagher, 2016). Technology specialization is a dual process of knowledge accumulation and articulation in science and technology-based disciplines (Nesta, & Dibiaggio, 2002). According to the results of this study, the subfields of Artificial intelligence, learning systems, and information retrieval are among the motor topics that are significant in training the skills of professionals in knowledge management-knowledge extraction. Therefore, defining courses for knowledge management students in universities can lead knowledge management with a forward-looking view in achieving their goals at the right time and place.

One of the factors in the formation of a new discipline of research is the increase in the number of publications in recent years (Seus & Bührer, 2021). The search results of the keyword knowledge extraction in Scopus show 4525 documents that have extracted knowledge. Of these, 3365 articles have been published in the field of computer science and 1611 articles and 2515 conference articles have been published. In the present study, the results of a study of 307 papers published in the field of knowledge extraction in knowledge management show that of these, the most articles have been published in the field of computer science (221), engineering (103), mathematics (50), decision science (49), business, management and accounting (44). Also, the exponential growth of publications and the growth of words from 1980 to 2022 show an increase in attention to these two areas together.

In the field of knowledge extraction, out of 307 articles reviewed, 50 articles are related to China and 49 articles to the United States. One of the reasons for China's success in global markets and economics is its efforts to follow the patterns of knowledge acquisition and development of knowledge-based industrial clusters (Oqubay & Ohno, 2019) and R&D (Jensen, 2014). One of the main factors in increasing the competitive advantage of different industries in China is the acquisition of domestic and foreign technology knowledge. Attracting talent from abroad and creating R&D cooperation with foreign companies are tools for acquiring knowledge in Chinese companies (Zhang & Gallagher, 2016). This could be proof of the fact that China is at the top of the list of countries that work in the field of knowledge extraction to create appropriate ways of using technological knowledge; and strives to train its staff in knowledge extraction and knowledge management.

In addition to the importance of universities and research centers in presenting a new discipline of research, a journal can help define a new interdisciplinary of research and facilitate its acceptance in the public face over time. A journal can provide a platform for progressing and advancing a specialized discipline of study by bringing together researchers and professionals. It also provides accessibility of research findings and research results to analysts and political and social policymakers by creating a space for researchers to access articles (Tarren-Sweeney, 2019). The results of the present study show that the Journal of Knowledge Management, at the top of the list, is a proper starting point among journals as it is active in publishing papers in the field of KE in KM. Therefore, it can help facilitate the creation of a knowledge management-knowledge extraction field as a pioneer in creating an interdisciplinary.

4. Discussion

The scientific growth of articles in the field of knowledge management has grown dramatically over the past few decades. The purpose of the application of bibliometrics analysis is the evaluation of published articles and the direction of the objectives of the articles. At the same time, according to the nature of knowledge management as a meta-disciplinary, the analysis and examination of different domains in the knowledge management process are considerable. Since without knowledge acquisition, the continuation of the knowledge management process is not possible, knowledge extraction as one of the preliminary phases requires attention and study. Therefore, the purpose of this study was to determine the state of publication of knowledge extraction in knowledge management. Collaboration between the countries of the USA and China is also mentioned in other studies (Gaviria-Marin et al., 2018; Ziyadin et al., 2019; De Bem Machado et al., 2022; Farooq, 2022). This could be due to the focus of universities and leading institutions on knowledge extraction in knowledge management, and defined policies to increase intelligence and digital processes.

There are close to 70,000 articles with the keyword of knowledge management in the Scopus database (Calof et al., 2022). Therefore, papers with a connection to two keywords of knowledge extraction and knowledge management have been chosen.

The importance of knowledge management along with other keywords in some bibliometrics studies has been considered. Most papers in the field of the study have been published in conferences proceedings. But it is worth noting that the Journal of Expert Systems with Applications, and Journal of Knowledge Management are the most active publications as mentioned in previous studies (Schiuma et al., 2020). The identified keywords in this study have been found in other research. knowledge management, Knowledge-based systems, Semantics, information technology, and Knowledge acquisition (Gaviria-Marin et al., 2018), ontologies, natural language processing, and knowledge extraction are among identified keywords that have importance in other studies (Chen & Luo, 2019; Basyal et al., 2020; Sawangwong & Chaopaisarn, 2021). Knowledge extraction, as the biggest challenge in different types of sources, is a crucial task in the knowledge management process. Graphs are also important and widely used tools to represent knowledge (Chen & Luo, 2019). Along with the advancement of technology and digitalization, knowledge extraction needs to be paid attention to as a critical phase of KM. It should be studied and designed for the types and formats of the data sources. This study shows the gap of study in the field of knowledge extraction phase in the knowledge management process by specialists in this field; while it is studied more in computer and information technology.

The results of the present study indicate that knowledge extraction in knowledge management is in the early years of life. Since knowledge extraction is based on artificial intelligence and technology, the results in the thematic map indicate that artificial intelligence and learning systems are the main topics for professionals and experts in KM-KE. However, considering the status of the KE phase in KM and its importance in the early stages of this process, it can be concluded that KE in KM is not well developed and this is a good reason to change the focus and attention on achieving and mastering this valuable knowledge. With the advent of industry 4 and the discourse of the emergence of industry 5, KM as a major requires the inclusion of various specialties and skills that can contribute to the development and success of this process in the future. Creating a new field in KM, ie KM-KE makes the process more flexible.

Stanley Katz (1996) argues that confining oneself to the rigid boundaries of a discipline prevents the emergence of many innovations and creations. The mission of today's universities is to process the questions of the time that require problem-oriented orientations and policies that are found in interdisciplinary academic structures (Shahamat et al., 2014). The current situation, given the nature and expectations of organizations and global markets and the issue of acquiring knowledge to achieve a competitive advantage, requires the creation of an interdisciplinary field called knowledge extraction. However, there are some limitations in this paper; In this paper, we present our interdisciplinary proposal based on the capabilities that are essential in the emergence of an interdisciplinary. Future studies by examining and comparing the papers published in WoS and the presented findings, the managerial and practical implications as well as the normative dimension of this view will be studied.

5. Conclusion

Given the nature of the field, professional knowledge acquired in a course has an average lifespan of 4 years. Due to the rapid progress, and emergence of new technology, the need to acquire skills and knowledge is strongly felt. Especially if the individual desires to get outstanding job positions (Enemark, 2002). One of the most important and influential disciplines in the life of organizations and the global economy is knowledge management and success in performing each of its stages. Knowledge management, like other disciplines, is changing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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