Knowledge and Information Systems (2020) 62:4481–4508
https://doi.org/10.1007/s10115-020-01492-x

REGULAR PAPER

A descriptive framework for the field of knowledge management

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Received: 22 November 2019 / Accepted: 6 July 2020 / Published online: 16 July 2020

Abstract
Despite the extensive evolution of knowledge management (KM), the field lacks an integrated description. This situation leads to difficulties in research, teaching, and learning. To bridge this gap, this study surveys 2842 articles from top-ranked KM journals to provide a descriptive framework that guides future research in the field of knowledge management. This study also seeks to provide a comprehensive depiction of current research in the field and categorizes these research activities into higher-level categories using grounded theory approach and topic modeling technique. The results show that KM studies are classified into four core research categories: technological, business, people, and domains/applications dimensions. An additional concern addressed in this study is the major research methodologies used in this field. The results raise awareness of the development of KM discipline and hold implications for research methodologies and research trends in the selected KM journals. The results obtained from this study also provide practitioners with a useful quality reference source. The framework and the components included provide researchers, practitioners, and educators with an ontology of KM topics, where they can cover deficiencies in research and provide an agenda for future research.

Keywords Knowledge management · Research direction · Literature · Grounded theory · Topic modeling · Text mining

1 Introduction

Knowledge is an important asset for organizations and the ultimate level in data hierarchy. Managing knowledge efficiently and effectively supports the decision-making process and helps organizations gain sustained competitive advantage [1]. Research exploring knowledge management (KM) is popular, where many journals, conferences, and outlets constantly drive

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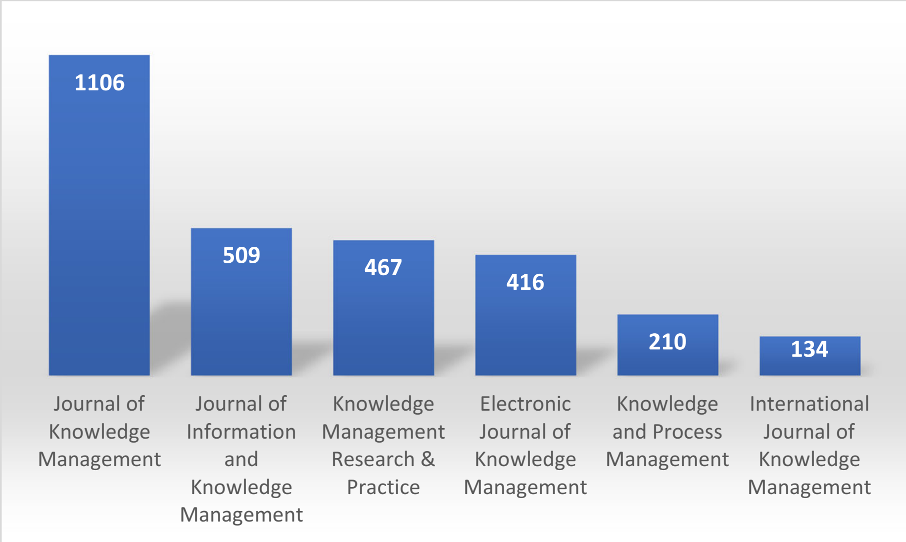

Fig. 1 Distribution of articles by journal

the research agenda and the evolution of this transdisciplinary field. However, researchers require a founding framework that guides research in the area of KM and helps in identifying different related issues.

The purpose of this research is to understand the prevailing directions or trends of KM research by analyzing titles, abstracts, and keywords listed in KM publications from selected articles. Given the high volume of articles used in this research, it would be a challenging task of reading the whole content of each paper [2]. Therefore, the research team collected for each article its title, abstract, and keywords and used text mining to analyze literature to address this difficulty. On a related note, several research studies analyzed literature using parts of the articles (e.g., title, abstract and keyword). For instance, Delen and Crossland [3] employed text mining on title and abstract of articles to analyze 1123 articles in management information systems area of research. Similarly, Bragge et al. [4] used text mining to analyze more than 15,000 articles' keywords in the field of multiple criteria decision making. Figure 1 shows the distribution of articles by journal.

This study intends to answer the following research questions:

1. What are the main research categories of KM field?
2. What are the core categories or themes?
3. What are KM research trends over time (1997–2017)?
4. What the research methodologies used in knowledge management literature?

This assessment will increase our understanding of KM discipline and establish paths for future research. The research process followed four stages. First, articles were extracted from the top-ranked KM journals as identified by Serenko and Bontis [5]. They are well-regarded knowledge management journals [6]. Second, titles, abstracts, and keywords were identified for each article, providing the foundation for text analysis. Third, grounded theory and text mining (topic modeling) were applied to answer the research questions. Fourth, descriptive analysis and topic modeling results were developed to identify the key KM research topics and trends.

Although previous research reviewed KM research directions (e.g., [7, 8]) and each study has its own focus, this is the first attempt to survey a large corpus of KM-related publications. In addition, this study provides a descriptive framework of the field of KM through comprehensive analysis of the KM research using grounded theory [9] and topic modeling approaches. A descriptive framework aims to capture the main research themes in this field. As a result, the findings inform academics and practitioners about the identity of KM discipline and open-up new opportunities to explore future research directions.

The organization of this paper is as follows: Sect. 2 presents the related work and research objectives. Section 3 discusses the research methodology. Results and analysis are presented in Sect. 4 followed by evaluation in Sect. 5, and finally, the conclusion is outlined in Sect. 6.

2 Related work and research objectives

Knowledge management is relatively young and an interdisciplinary field [7]. The examination of this discipline will lead to an improved understanding of KM domain. Reaching a common KM understanding supports the establishment of its identity [10] and also contributes to the organizations that intend to implement knowledge management system in their organization [11]. Past literature stresses on the importance of KM system for organizations as it supports organizational learning through sharing both tacit and explicit knowledge [12].

KM system can be described from the technical perspective and socio-technical perspective [12]. From the technical perspective, KMS can be described as IT infrastructure in terms of software and its associated hardware. Technology-centered KMS involves a variety types of technologies such as groupware, data mining, visualization, and decision support system for supporting organizational learning and knowledge work. Under the perspective of socio-technical, KMS is more than technology. It is viewed as a combination of technology infrastructure, organizational infrastructure, culture, knowledge, and people.

Speaking practically, developing frameworks for the field of knowledge management provides organizations the guidelines that are crucial to implement KMS in order to avoid errors and gain benefits in terms of time and cost involvement [11].

Therefore, it is warranted to continue the examination of this field [7]. Consequently, several studies reviewed the KM discipline and tried to enhance the understanding of this domain by analyzing pertinent publication samples. The focus of such studies ranges from identifying the main research topics being addressed in KM literature, research methods that are used in KM research, or the most cited papers in a sample. Some research explored more than one of the previously mentioned issues.

For instance, Walter and Ribière [8] investigated the main research issues addressed by 256 articles published in Knowledge Management Research and Practice (KMRP) journal. Another example is the study of Fteimi and Lehner [13], who applied CA-based review to identify key research topics of 755 publications published in the proceedings of European Conference on Knowledge Management (ECKM). Serenko and Bontis [14] tracked the citations of 63 KM-related articles published in the Journal of Knowledge Management (JKM). However, the focus of these reviews was on individual journals.

Further, Serenko and Dumay [15] analyzed the attributes of KM citations in seven KM-centric journals. Moreover, Serenko et al. [16] conducted a scientometric analysis of 2175 articles published in 11 major knowledge management and intellectual capital (KM/IC) journals (1994–2008). Wallace et al. [17] applied a bibliometric and content analysis to explore research methodologies that are used in knowledge management-related articles.

Similarly, through a meta-analysis approach, Dwivedi et al. [18] investigated the research paradigms and research topics of KM-related studies between 1974 and 2008. Handzic [7] also examined the research issues and approaches in key KM journals. Using citation and co-citation analysis, Ma and Yu [19] also explored the research paradigms of contemporary knowledge management studies.

Unlike previous studies, this paper employed the grounded theory and text mining approach (topic modeling) to track the evolution and research trends of KM domain over time (1997–2018) and provided a descriptive framework for the field of KM. The review is based on six top-ranked KM journals.

3 Research methodology

Research depending on the review of prior articles is critical for strengthening a field of study and provides important input for shaping future research [20]. Researchers can use a number of methods to review a body of research literature ranging from qualitative to quantitative [21].

To answer the research questions, we employed a descriptive review of relevant KM published research. Descriptive review concerns with revealing an interpretable pattern [21]. Generally, descriptive analysis of prior studies often introduces some quantification in the form of frequency analysis including trend analysis and cluster analysis [22]. This style of research enables tracking science evolution [7] by examining keywords frequencies [23] and word cluster analysis [8]. The following section describes the procedure for conducting this descriptive review.

3.1 The article sample

The first step of reviewing the existing research literature is to find relevant literature through computer and manual searches, and this can be done by identifying some distinguished journals and conferences [24]. Therefore, for a literature review on KM, six reputable KM journals were targeted: Journal of Knowledge Management, Journal of Information and Knowledge Management, Knowledge Management Research and Practice, Electronic Journal of Knowledge Management, Knowledge and Process Management, and the International Journal of Knowledge Management. According to Serenko and Bontis [5], these journals are in the top-ranked journals in KM domain. Consequently, we felt that these outlets are adequate for representing the state of a research domain.

The total number of articles used in this study is 2842. The research team collected for each article its title, abstract, and keywords. Each journal has its own time frame because of its starting year and availability. The time period under investigation for each journal is as follows: Journal of Knowledge Management (1997–2017), Journal of Information and Knowledge Management (2002–2017), Knowledge Management Research and Practice (2003–2017), The Electronic Journal of Knowledge Management (2003–2017), Knowledge and Process Management (1999–2018), and the International Journal of Knowledge Management (2005–2017). Figure 2 presents the distribution of articles by year.

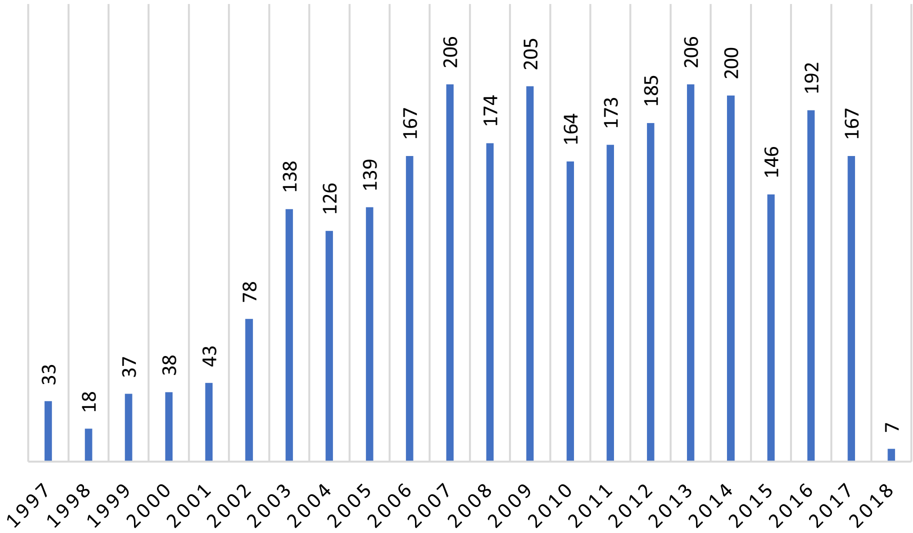

Fig. 2 Distribution of articles by year

3.2 Grounded theory approach and topic modeling

This study applied grounded theory approach using text mining (topic modeling) to systematically reveal and examine important insights in KM research. Grounded theory is commonly used as a method for reviewing literature [24–26]. It is a widely accepted approach in many fields such as educational studies, organizational research and information systems to develop theories and frameworks [25, 27, 28]. We adopted grounded theory in this research for the following reasons: this research aims at identifying the major categories and sub-categories to propose a descriptive framework for the field of knowledge management using the existing KM literature. Grounded theory as an inductive methodology was designed to serve such purpose. Moreover, in the literature, grounded theory is proven to be used to develop the theoretical framework in related disciplines. For instance, Peng et al. [29] adopted grounded theory to generate an integrated framework for the field of data mining. Yang and Tate [24] used grounded theory to develop a classification schema for cloud computing research. In addition, Bacon and Fitzgerald [30] applied grounded theory to develop a systematic framework for the information system field. Grounded theory is a qualitative research method used to provide systematic and detailed data analysis. It is a systematic classification process of coding and identifying categories, sub-categories, and the relationships between these categories. Topic modeling, on the other hand, is a quantitative text mining method utilized to generate codes or labels of the underlying data [31]. In recent years, the relationship between qualitative and quantitative research approaches in the form of mixed methods research has gained momentum [32, 33]. This approach calls for possible forms of interrelation between both quantitative and qualitative approaches within a single study [32]. Simultaneously, qualitative research itself has been critiqued for self-reflexive issue [33]. Some qualitative approaches such as the traditional grounded theory have been also critiqued for the large amount of human time and energy required in data analysis [34]. Particularly, due to large sample size of data, qualitative coding using such method becomes a labor intensive and time-consuming task even if manual coding is replaced by computer-assisted coding tools

[32]. Consequently, the traditional grounded theory as introduced by Glasser and Strauss has witnessed major reconfigurations [33]. In turn, some research studies have revealed interesting linkages between grounded theory and quantitative text mining methods, such as topic modeling [35, 36]. Grounded theory equipped with topic modeling is useful in facilitating the coding process and would enhance the rigor and reliability of the analysis through minimizing the preconception and subjective analysis as in human coding process. In this work, we seek to combine the strengths of both techniques (grounded theory with topic modeling) to generate a novel approach. Our main argument is that topic modeling in the grounded theory approach provides more objective approach for researchers interested in working with qualitative data. Consequently, this would improve inferences quality within qualitative research especially when working with large data sets (e.g., thousands of documents) [33]. The main objective of using grounded theory and topic modeling is to build a descriptive framework that identifies categories and the core themes for the purpose of enhancing our understanding of the phenomenon being addressed.

3.2.1 Grounded theory approach

The first stage of carrying out the grounded theory method is data collection [37], and the first step of data analysis in grounded theory is open coding. Open coding is a descriptive process that involves generating initial concepts based on the data. In this study, we applied topic modeling to automatically conduct open coding and reveal the initial or preliminary codes. The outcome of this stage is the initial concepts emerging from the data. The second stage is axial coding, which involves linking the concepts into higher-level categories. The final stage is selective coding, which involves linking the generated categories into higher core themes or categories. These steps are used in sequential and iterative ways. In addition, the analysis procedure should keep the coding process active using constant comparison to compare and contrast the similarities and differences in the qualitative data in order to identify patterns in the data. In the constant comparative method, analysis should examine two standard questions: "what is happening in the data?" and "what action does each particular happening, incident, event or idea represent?" The purpose of investigating these questions is to identify categories and relationships between and within categories [38].

3.2.2 Topic modeling algorithm

Topic modeling is unsupervised text mining algorithm for discovering the topic that pervades a large collection of documents. It increasingly has become popular for automatic documents summarization into a fixed number of topics [31]. Topic modeling automates the process of open coding in which any prior labeling of the text is not required. The main advantages of this algorithm include: First, objectively coding the data without being affected by any uncontrollable variables such as carelessness, boredom, and other emotional status [39]. Second, it is considered as an appropriate replacement of manual coding of large data collections that require intensive labor work [35, 40].

The major steps of topic modeling include data pre-processing and involve tokenization, converting to lower case, and removing stopwords. Tokenization breaks documents into words/phrases. Converting documents to lower case allows to use same capitalization of the words. Stopwords are common in all documents such as article, prepositions, and conjunctions. Pre-processing is critical task as it removes a lot of noises and hence increases the efficiency of topic modeling algorithm. Next, each document is represented using well-known

Term Frequency Inverse Document Frequency (TF/IDF) weighting schema [41]. Particularly, Term Frequency Inverse Document Frequency (TF/IDF) weighting schema is calculated for each document. Term frequency counts the frequency of a particular word in a document. Inverse document frequency metric is also considered and can be calculated by taking the total number of documents (N), dividing it by the number of documents containing a word (DF), and then calculating the logarithm of that quotient log (N/DF). IDF value is used to represent how common or rare a certain word appears in a collection of documents. The TF-IDF value reflects how important a word is to a document in the corpus. Next, a topic modeling algorithm will be used to organize the text documents according to the discovered topics. This study chose latent Dirichlet allocation (LDA) algorithm [31] to identify latent topic from documents, and Python software to perform topic modeling. LDA constitutes the most common algorithm to discover the main themes or topics from a large collection of documents due to its conceptual advantage over other topic models [31]. This model assumes a generative process for deriving probabilistic topic models from a collection of documents. The basic idea of LDA is that documents can be viewed as random mixtures over hidden topics, where each topic is represented by a distribution over words. To further illustrate the results of LDA, let D be the number of documents in a collection, T is the number of topics, and W is the number of words in a document. A $D \times T$ matrix contains the association between a document and a topic, and $W \times T$ contains the association between a word and a topic. In the generative process for each document, a multinomial topic distribution θ is randomly sampled from Dirichlet with parameter α, and then to generate a word, a topic is chosen from this distribution over topics, and a word is picked by randomly sampling from the chosen topic [42].

The topics retrieved using this LDA model have been described as informative with respect to the actual topics discussed in the text corpora (documents) under study [32].

Figure 3 shows the process of the analysis as detailed below.

The process of grounded theory using topic modeling analysis took place in the following steps. First, the process started with collecting research data (publications' title, abstract, and keywords) in the time span between 1997 and 2018. All collected data were saved in one big ".csv" file, and we treated each publication metadata as one document. For this paper, Python www.python.org was utilized to run LDA topic modeling, since it is a popular and widely used language for text processing, open source and provides a high flexibility through the use of its packages [43].

Second, we partitioned the whole dataset into three different corpora based on the associated "publication year" variable. This separation was necessary to track the evolution and research trends of KM research over time and answer the research questions. The first corpus contained data from 1997 to 2003, and the second corpus contained data from 2004 to 2011, while the third one contained data from 2012 to 2018.

In the third step, we performed some transformation on each corpus for easier data processing. In particular, all publications titles, abstracts, and keywords in each corpus were harmonized to lower case to keep consistency in the results. Numbers, punctuation, and stop words were removed from the dataset as they do not provide value to the analysis

Next, this study applied topic modeling (LDA) algorithm to automatically generate codes from the analysis of the raw data. The generated topics were based on articles' titles, abstracts, and keywords. Based on trial and error approach, the number of topics was set to 10 in each time span. Figure 4 depicts the topic modeling procedure.

In axial coding stage, we examined the initial topics revealed by LDA. These low-level topics or concepts were grouped into more general categories. We revised the categories iteratively to make sure they represent the main concepts generated by LDA (open coding

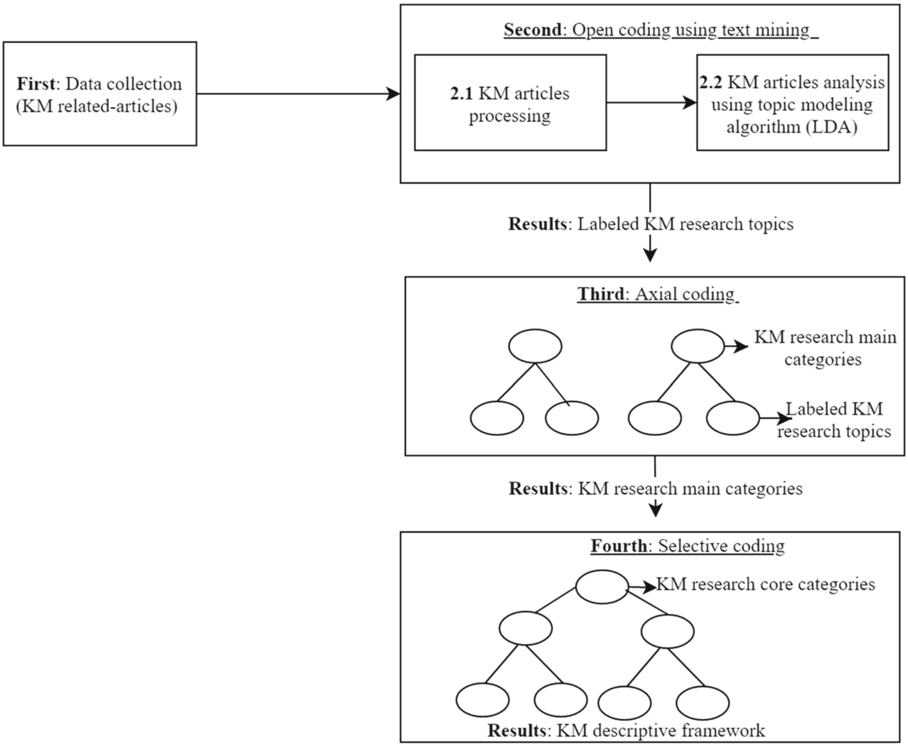

Fig. 3 Literature analysis process

Input:	**2842 articles**
Output:	**classification schema**
Start Procedure	
Step 1	Extract titles, abstracts and keywords of the collected articles and tokenize them into words or phrases
Step 2	Harmonize all words to lower case and remove stop words, number, and punctuation.
Step 3	Use LDA algorithm.
Step 4	Fit a 10-topic LDA model.
Step 5	Name the discovered topics.
Step 6	Continue to axial coding and selective coding stages.
End Procedure	

Fig. 4 Topic modeling process

level) [29]. In selective coding stage, we grouped all generated categories in axial coding further into more general and most applicable themes or core categories [29].

3.2.3 Word frequency analysis technique

To answer the fourth research question pertains to the research methodologies used in KM research, a word frequency analysis was conducted to retrieve the frequencies of the predetermined list of popular research methodologies used in the literature. Under the research methodology, literature distinguishes between research methods and research designs or approaches [44]. In other words, research methodology determines the types of research approaches and research methods that may be deployed to answer the research questions. Previous studies treat research methods as techniques for data collection such as questionnaires, interviews, document analysis, and observation [44–46]. Research approach or design, on the other hand, refers to the ways of designing and conducting research such as qualitative approach, quantitative approach, and mixed methods design or approach [44]. Examples of qualitative research approaches mentioned in the literature include qualitative case study, grounded theory, ethnography, content analysis, phenomenology, and action research [45, 46]. The major quantitative research approaches include survey and quantitative case study.

After determining the popular research methodologies deployed in the literature, we then conducted term frequency analysis on the title, abstract, and keywords to retrieve the frequency counts of a specific methodology. Numerous scholars employed lexical analysis such as word frequency count to examine the research methodologies deployed or the research trends in a specific field (e.g., [13, 47]).

4 Results and analysis

This section describes how topic modeling and grounded theory were adopted to develop a descriptive framework for the KM field.

4.1 Open coding

Open coding phase includes labeling phenomena, discovering, and naming categories [9]. Labeling phenomena involve identifying the concepts and ideas from documents (datasets). As aforementioned, this study applied topic modeling (LDA algorithm) to identify concepts and organize the extracted concepts into topics (a set of concepts). Table 4 ("Appendix A") represents the open coding (LDA results) for all periods of time.

4.1.1 Topics labeling

Before using the topics generated by topic modeling algorithm to develop KM descriptive framework, each topic needs to be labeled to specify what constitutes the homogeneity of that topic. Topic labeling aims at selecting a representative name or title to provide a better understanding about the semantic of the topic, i.e., providing a single label that interprets a list of words relevant to a particular topic [48, 49]. As LDA is unsupervised algorithm for discovering topics, the process of assigning labels or titles to topics is usually performed manually especially when labeling demands domain knowledge to ensure high labeling quality [42, 50]. Therefore, we manually inspect the top ten words/concepts of each topic to identify the main theme of that topic. This is important as it distinguishes each topic from another. Naming topics process involved reviewing the concepts under each topic and comparing the topics. These steps are necessary in order to abstract the concepts that adequately describe the underlying concepts. The following topic resulted from LDA algorithm in the first term (1997–2003) was used to illustrate how the topic labeling was performed.

> Topic (Performance Measurement): *[KM, performance, measures, government, KMS, organization, scorecard, balanced, capital, transfer]*

In this topic, the top ten retrieved words/concepts were used to find out the key issue of this topic and assign a representative label to it. In particular, the concepts *[performance, measures, scorecard, balanced]* are all related to performance measurement. Moreover, looking into the frequency of these concepts into the first term dataset, we found that performance has frequency 106, 43 for measures/measurement, scorecard frequency is 14, and 8 for balanced scorecard.

We also found 16 articles in the first period (1997–2003) dataset addressed performance measurements issue linked to KM, KMS, and organizations that used KMS. These concepts *[KM, KMS, organization]* also appear in the above topic.

The following section represents a discussion on the topics identified in the datasets. Table 1 also presents topics related terms frequencies in the whole dataset.

First term (1997–2003)

- *Performance measurement* This topic unveils the interest of measuring the performance of knowledge management systems (KMS) to obtain all KM benefits and achieve organization's objectives. Several tools and techniques are proposed to measure KMS performance in the literature. One of the well-known techniques is balanced scorecard as it provides a comprehensive approach to performance measurement of KM.
- *Intellectual capital (IC)* It is a popular term in KM literature. KM and IC are key research streams. These topics are examined together to reflect how IC (knowledge resources) and KM (processes) help organizations achieve their goals in terms of performance, value, learning, and innovation.
- *Organizational learning and learning organization* Another commonly research topic. Such work focused on the relationship between organizational learning (OL) and KM as well as the relationship between KM and learning organization (LO). The supportive culture, the required infrastructure, and KM initiatives (in terms of creation, sharing, and utilizing knowledge) would help organizations embed knowledge into organizational processes [51]. This is necessary to help organizations pursue the achievement of their goals and transforming the organization into the LO.
- *Information technology* Another prevailing topic investigates the role of information technology in knowledge management as an enabler of KM. IT tools are essential in KM program as IT provides the necessary capabilities that support knowledge management processes (knowledge creation, sharing, and application).
- *Knowledge management systems (KMS)* It is a well-discussed topic within KM literature. Such work focused on exploring the importance and the role of designing KMS to support management of organizational knowledge. Databases, information architecture, IT, tools for learning, and adequate organizational support are all necessary elements in KMS to support various KM processes. The benefits extend beyond managing knowledge to also include developing competitive advantage.
- *Innovation* It presents organizational innovation. Studies related to this topic examined the contribution of KM to organization's ability to innovate and compete. Several models and theories are applied to assess this link.
- *Knowledge workers* It focused on managing human capital as it forms the main asset for many organizations. The literature also investigated the role of KM in empowering human resources in organizations. It is considered as a key pillar in human capital strategy.
- *Knowledge economy* Is a well-studied topic in KM literature. Such work focused on the concept of knowledge-based economy and viewed knowledge as one of the main organizational assets. Similar studies also investigated knowledge workers, where they are an

Table 1 Topics frequency count by years

Topics/frequency	First period	Second period	Third period	Total
Knowledge discovery	14	25	10	49
Analytics	0	6	2	8
Big data	0	0	137	137
KM visualization	4	18	30	52
Data mining	11	52	88	151
Total	29	101	267	397
KMS	70	101	115	286
Knowledge management system	43	167	127	337
KM tools	2	10	38	50
Information technology	44	74	82	200
ICT/IT tools	3	75	97	175
Total	162	427	459	1048
Intellectual capital	67	359	404	830
Organization learning	33	41	65	139
Innovation	121	420	929	1470
Knowledge worker	61	70	82	213
Knowledge economy	25	64	40	129
Tacit and explicit knowledge	58	369	304	731
Community of practice	4	46	38	88
Personal knowledge	0	21	40	61
Total	369	1390	1902	3661
Performance measures/balanced scorecard	23	33	44	100
Knowledge engineering	8	3	9	20
Online knowledge sharing	0	3	3	6
Knowledge sharing	44	619	1119	1782
KM process	2	14	33	49
Knowledge exchange	7	27	53	87
Knowledge creation	55	249	268	572
Knowledge acquisition	12	54	73	139
Knowledge elicitation	4	15	17	36
Knowledge transfer	41	424	413	878
Knowledge generation	1	25	11	37
Knowledge application	6	14	18	38
Total	203	1480	2061	3744
Promote KM programs (reward, incentive, motivation, culture)	119	515	508	1142
KM readiness	6	8	63	77
Total	125	523	571	1219
KM barriers	23	111	159	293
Total	23	111	159	293
Industry	59	231	214	445
Knowledge city	0	29	7	36

Table 1 continued

Topics/frequency	First period	Second period	Third period	Total
Ontology	2	107	94	203
Subsidiary knowledge	0	0	7	7
Knowledge marketing/customer knowledge	10	20	41	71
Total	12	387	363	762

important element in knowledge economy. It is also noted that culture is an important issue in this knowledge economy era.

- *KM processes* Another prevailing topic is related to studying KM processes (knowledge creation, knowledge sharing, and application). Basically, KM focuses on knowledge-based processes to utilize knowledge-based resources as a source of leveraging organizational performance.
- *Tacit and explicit knowledge* Several studies investigated tacit and explicit knowledge types, ways to acquire, share, and apply knowledge, and challenges faced in sharing or transferring knowledge.

Second term (2004–2010)

- *Knowledge discovery* Several studies investigated knowledge discovery process using modern techniques of data mining. The importance of KM encouraged researchers on focusing on acquiring knowledge by discovering it inside or outside organizations.
- *Knowledge city* It is a widespread topic in KM literature. This topic investigates knowledge city as a subfield of knowledge-based development. Related concepts are knowledge workers, knowledge economy, intellectual capital, knowledge capital, human capital, and learning organizations.
- *KM barriers* KM literature also thoroughly examined KM implementation barriers. Several quantitative and qualitative studies investigated barriers to KM processes (creation, sharing, and application), barriers impacts, and barriers identification and management.
- *Promote KM program* Another prevailing topic addressed the ways to promote KM projects. Related concepts are motivation on knowledge sharing and creation, cultural and social issues for knowledge sharing, attitudes, reward systems, community of practice, etc.
- *Community of practice (CoP)* KM literature on CoP investigated topics such as knowledge sharing in CoP, virtual community of practice, motivation, KM practices in CoP, and performance.
- *KM tools* Several studies investigated KM tools and technologies and their usage for enabling collaborative relationships and supporting different aspects of KM. This includes mobile technology, video conferencing, and other ICT tools.
- *Readiness for KM* KM literature also highlighted the issue of KM readiness. Basically, organizational change, organization's readiness for KM project, and readiness for change are some of the issues discussed under this topic.
- *Organizational learning* Is one of the hot topics that have been addressed over time in KM literature. It is more related to the learning organization topic.
- *Industry* Examining KM topic in different industries was one of the well-covered topics. The research under study addressed KM topic in various sectors or industries such as: healthcare, banking, education, mobile telecommunication companies, tourism, and film industry.

– *Ontology* It is one of the important topics that have been addressed in KM literature. Ontology-based models to support KM implementation. Examples of the addressed topics: ontology for identifying organizational competencies, ontology for knowledge sharing and reuse, ontology for collaborative knowledge management network, ontology for knowledge audit in organization, and ontology development and evolution.

Third term (2011–2018)

– *Knowledge engineering* KM literature investigated important issues related to developing ways to transform existing knowledge to be used effectively (i.e., knowledge engineering). Related topics include knowledge codification, knowledge sharing and transfer, knowledge elicitation, and barriers for transfer of codified knowledge.
– *Subsidiary knowledge* Another important topic is transferring subsidiary knowledge (subsidiary to parent knowledge flow). Key-related concepts that have been investigated: knowledge flow, knowledge transfer, learning, multinational companies, transfer performance, transfer behavior or intention, and green innovation.
– *Analytics* One of the hot topics in KM literature is analytics. Such work addresses data and text mining, big data analytics, business analytics, web security, knowledge discovery, semantic knowledge, and ontologies.
– *Big data* The link between big data and knowledge management has received considerable attention. Important subtopics that have been investigated were data, information, big data, analytics, data mining, learning, competitiveness and sustainable entrepreneurship, and big data in personal knowledge management (PKM).
– *Innovation* This topic and its related concepts, such as: performance, intellectual capital, green innovation, knowledge quality, knowledge sharing, entrepreneurialism, are all covered under this topic.
– *KM visualization* One of the prevailing topics in KM literature is visualization. It is essential for knowledge creation, transferring and sharing knowledge in a wide range of contexts. Related concepts include modeling, knowledge mapping, and visualization techniques.
– *Personal knowledge* It addresses personal knowledge management (PKM) and knowledge creation tools, PKM tools, learning, knowledge worker, knowledge management generation, and big data.
– *Online knowledge sharing* Computer-mediated communication, knowledge sharing behavior, knowledge sharing context, attitudes, knowledge sharing barriers (KSBs) were all important concepts investigated under this topic.
– *Data mining* The link between data mining and knowledge management also received considerable attention in this term.
– *Knowledge marketing* One of the important topics in this period. Related concepts include customer knowledge management (CKM), capture/share/utilize customer knowledge, knowledge flow, retention strategies, knowledge intensive firms, and entrepreneurial firms.

It is worth mentioning that the topics are not mutually exclusive [29]. For instance, KM concept appeared in more than one topic such as performance measurement, organizational learning, knowledge management systems, etc. Therefore, some topics exhibited some overlaps. On the other hand, the discovered topics should be further modified and combined through asking questions and comparisons. For instance, knowledge discovery topic in the second term should be combined with data mining and analytics topics in the third term as they refer to similar research area. The topics we initially identified in open coding are reduced to eight categories [9]. This is illustrated in axial coding stage. The output of open coding stage answers the research question in this study: What are the current research themes in the field of KM?

For KM research trends over time, some research directions continued to appear in the three time periods. This is based on the results of open coding stage using topic modeling. For instance, learning, innovation, KM technologies or tools existed in the three time periods. On the other hand, some research topics started to be popular in late periods. For example, in the second and third period of time, data portrayed more focus on knowledge discovery, data mining, big data, and analytics concepts.

4.2 Axial coding

The axial coding involves linking categories and their sub-categories in order to gain better understanding of the phenomenon under study [37]. Thus, axial coding stage involves further grouping of similar sub-categories (topics) under more general categories. In this study, axial coding refers to linking topics, where we grouped topics in all time intervals generated by open coding stage into a number of code clusters. The last stage involves reviewing, comparing, and contrasting the thirty topics generated from open coding process into eight categories. This categorization is based on assigning a single category that is most applicable to a set of related topics. For instance, [knowledge discovery, analytics, big data, KM visualization, and data mining] topics were all abstracted under [KM analytics] category. These clusters/categories were developed based on the meaning of the codes, reviewing them, and comparing and contrasting these codes. Actually, constant comparison is the key in the process, where we discover the latent patterns and their conceptualization [52].

Figure 5 portrays the classification schema. This schema depicts the process of abstracting the concepts and categories into higher-level categories. Level 1 shows the generated KM topics (the output of open coding stage). We then clustered these topics into more general KM categories and placed them at level 2 (axial coding stage). We further grouped these KM categories into more general conceptual KM dimensions (selective coding stage): technological dimension, business dimension, people dimension, and domains/applications dimension. Particularly, KM analytics and KM technologies were abstracted into technological dimension. Intangible assets, KM management/process, managerial actions, and personal/managerial issues were grouped under business dimension. Personal issues were abstracted under people dimension. Finally, knowledge-based ontology and KM context were grouped under domain/application dimension.

KM analytics This category focuses on analytics as an enabler of KM, and important means to visualize and analyze data. The sub-categories include: knowledge discovery, analytics, big data, KM visualization, and data mining [53, 54].

Intangible assets This category consists of sub-categories related to intangible assets components and include: intellectual capital, organizational learning [55], innovation [56], knowledge workers [57], knowledge economy [58], tacit and explicit knowledge, community of practice, and personal knowledge [59].

KM management/processes This category includes sub-categories that addressed KM processes and KM measurement: performance measures, KM processes, knowledge engineering [60], and online knowledge sharing.

Managerial actions This category concerns with the managerial practices required to promoting KM programs and organizational readiness for knowledge management [61, 62].

Personal/managerial issues This category focuses on KM barriers. KM barriers could be categorized based on individual and organizational levels [63]. This categorization is also

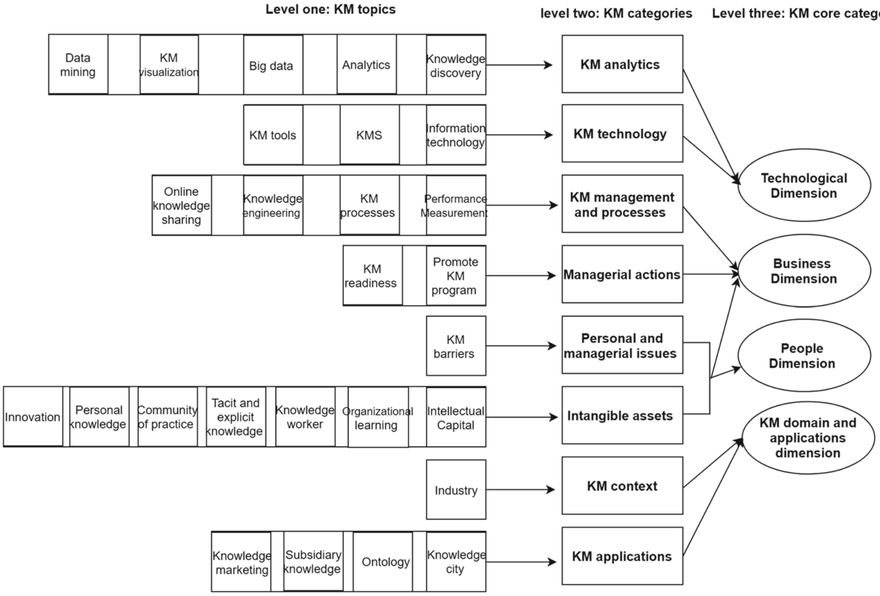

Fig. 5 KM classification schema

reflected in the selective coding process where this category belongs to business and people dimensions.

Applications This category includes sub-categories concerning knowledge applications in a particular area. Examples of sub-categories: knowledge city, ontology-based knowledge, subsidiary knowledge, and knowledge marketing.

KM technology This category focuses on the technological aspects of KM such as information technology, knowledge management systems, and KM tools [64].

KM context This category concerns the impact of KM on specific industries or sectors.

The mappings between categories and core categories are often one-to-one. For example, “KM analytics” category was mapped to “Technological” dimension. However, there are also some KM categories correspond to multiple categories. For instance, “Intangible Asset” category was mapped to “Business” and “People” dimensions.

4.3 Selective coding stage

Selective coding is the process of selecting a core category and relating other categories to it [37]. Core category/s represent the main phenomenon of the study. The process of selective coding resulted into four KM dimensions: technological, business, people, and domain/application dimensions. This answers the research question, what are the core categories or themes of KM field.

Technological dimension This core category focuses on technology details of knowledge management. It includes IT tools and knowledge management systems applied to manage knowledge within organizations and support KM processes (creation, sharing, and application).

Business dimension This core category concerns with the business implications of KM implementation in organizations. Articles under this category focus on all categories related to intangible assets management, KM processes, management practices to support knowledge management, as well as managerial issues.

People dimension This core category includes KM research studies which address people related factors like personal knowledge management and knowledge worker, their trust, believes, and attitude toward KM [65].

Domains/applications dimension This core category contains articles concerning the impact of KM in particular domains as well as domain ontologies that can be used to facilitate knowledge organization and interchange in specific areas [66].

Figure 6 presents a descriptive framework of the field of KM. The figure visualizes the four dimensions and their categories. Specifically, this framework classifies KM literature into four core themes or dimensions. Building upon topic related term frequencies (shown in Table 1), the literature analysis revealed that business dimension-oriented articles outnumbered other dimensions-focused articles. Under this category, intangible assets and managerial issues have received much focus by researchers [13]. It is also important to admit the notion of blurred borders; the dimensions-related articles have overlaps. For instance, in intangible assets category: knowledge workers, intellectual capital including human capital, and community of practices overlap with people dimension. In addition, the interaction between the core categories (dimensions) is noticeable. Considerable evidence can be found that technology, people, and management should be put together if an organization seeks for better manage of knowledge and leverage its performance [65]. Knowledge management is not an independent organizational phenomenon. Specifically, organization and its members may be engaged in knowledge management processes, and the supporting IT tools form the solid foundation for knowledge management and can increase the breadth and depth of knowledge management processes [64]. Therefore, knowledge management is a multi-disciplinary venture where it requires synthesis among management, people, and technology to support organization's objectives in specific domains [67].

4.4 Distribution of topics by years

Based on topics distribution by years, business dimension-related categories and topics are clearly the top studied area in knowledge management. Under this dimension, the most heavily published research topics in all three time periods are intellectual capital, innovation, tacit and explicit knowledge in intangible asset category and knowledge sharing, knowledge creation, and knowledge transfer in KM processes category. A remarkable increase in the research studies harvesting these topics through KM reveals a strong interest in focusing on non-tangible assets perspective making it a productive and attractive area of research. Literature shows that knowledge management and intellectual capital as a very attractive domain among academics and practitioners that has been continuously growing [14]. There is also an increasing attention to explore the link between company innovative capacity and knowledge, knowledge types, and KM processes. Literature shows that knowledge is the key source for continuous innovation and success [68, 69]. It is interesting to dig deeper into this discipline in knowledge management and design the appropriate tools to measure the impact of knowledge management innovation on organizational outcomes [30].

It is also worth mentioning that knowledge sharing is the most discussed topic across all categories according to our classification. Literature views knowledge sharing as a building block for organizational success and survival [68]. On a related note, research on the role of new technologies including web 2.0 and social networking such as Twitter, Facebook, and blog on knowledge sharing and transfer has also received growing attention by time, Yet,

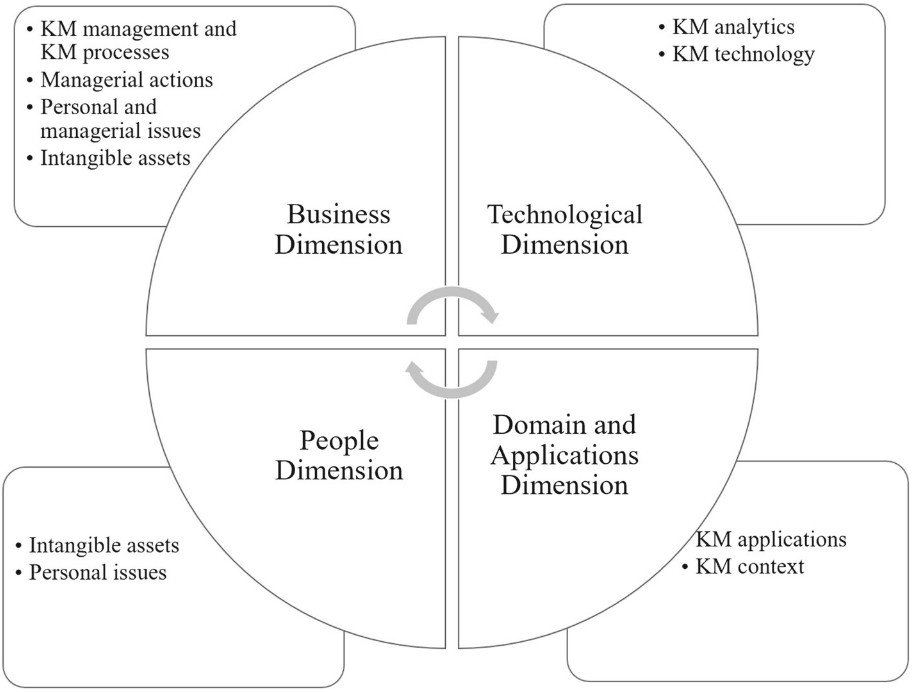

Fig. 6 A framework for KM field

there is still much to study about the use of social networking in knowledge sharing or online knowledge sharing in different organizations and cultural contexts [70, 71].

Promoting KM program is also exhibited an increasing trend in KM studies. Literature extensively studied reward system and motivation and the culture that support these variables due to their importance in governing individual attitude and behavior toward knowledge management initiatives.

Further, people dimension-related topics and categories have gained a growing interest during the second and third time periods. Literature has investigated key KM barriers that adversely affect the success of KM implementation in organizations. As mentioned previously, KM barriers factors can be associated with people and organizations. These factors include lack of familiarity with the subject, lack of knowledge, lack of motivation, staff retirement, management support, technological infrastructure, organizational culture, organizational structures, and other readiness related factors [71, 72].

As aforementioned, the dimensions-related articles have overlaps. For instance, intellectual capital, innovation, knowledge workers, community of practices, etc., in business dimension overlaps with people dimension as these topics are dealing with human aspects of KM as well.

In technology dimension, it is unsurprising to see knowledge management systems, KM tools, ICT and IT tools have received an increasing attention as technology is one of the key cornerstones of knowledge management [65]. However, under technology dimension, we notice that KM analytics is an under-explored area. This category has recently gained KM researchers interest. As shown in Table 1, big data, data mining, and KM visualization attract more attention in the third time period. It is reasonable to predict that KM analytics category

Table 2 KM domains/applications frequency count

KM domains/applications	Frequency count
Higher education/university	477
Banking industry	154
Healthcare	111
Telecommunication	45
Consulting	70
Hospitality and tourism	25
Other domains	203

is an emerging area of research and will continue to be a hot topic in knowledge management field [73]. It is a promising new area of research and future lines of research may focus on big data analytics, KM capabilities, and KM analytics culture development in organizations.

Table 1 also shows a growing research attention in the domains and applications dimension. Industry topic is a popular research area under this dimension. By exploring the whole dataset, we found that KM researchers have studied knowledge management-related themes in several industries. Table 2 shows the industries that have been examined in the context of KM and their frequency count in the whole dataset. These industries include higher education/university, banking, healthcare, telecommunication, consulting, and hospitality and tourism. Other domains include e-government, semiconductor, automotive, manufacturing, service, financial, exchange trade, biotechnology, oil and gas, construction, insurance, nuclear power, high-tech, software, airline, defense/aerospace, railway, water supply, accounting, retailing, and music industry. As shown in Table 2, we notice that KM in higher education has the most frequency count across all aforementioned industries. This indicates the potential of implementing KM initiatives in universities. KM has been seen as an important vehicle for innovation and development in higher education [74]. Future lines of research may investigate other under-explored domains such as the role of KM in start-up businesses.

4.5 Analysis by KM research methodologies

Research methodologies are an essential component of a scientific research to achieve valid and reliable study results [13]. In this study, we employed a word frequency count method to identify the research approaches and methods applied by KM researchers in the selected KM journals. In order to report accurate results with respect to the frequency count, we set the maximum number of the frequency count of a particular research method or approach in each document (article's title, abstract, and keywords) to one. For instance, if "survey" research approach appears more than one time in the article's (title, abstract, and keywords), that number was reduced to one.

Figure 7 outlines the frequency count of the used research approaches in all three time periods. The results showed case study is the most favored research approach. This result is consistent with past observations as in the studies of [7, 17] in which case studies were the most used research design in KM research. Survey design is the second commonly deployed approach. This finding is consistent with [15] study in which surveys followed case studies in popularity. Experimental studies are far less popular than case studies and survey designs. Ngulube [44] study confirmed the limited number of studies that employed experimental design in KM field. Worth noting, the findings also revealed the gaps in using some research

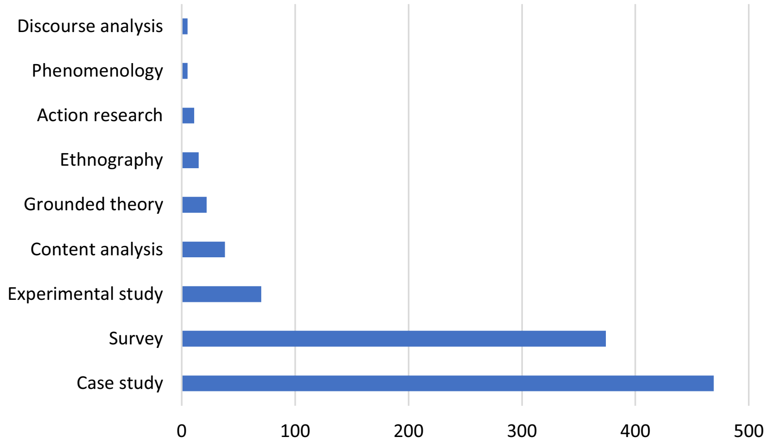

Fig. 7 Frequency counts of the research approaches used

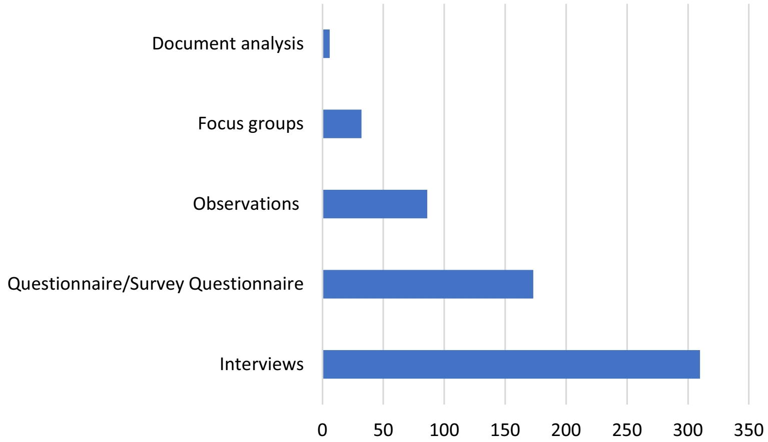

Fig. 8 Frequency counts of the research methods used

approaches. Specifically, major research approaches such as action research, ethnography, phenomenology, and discourse analysis were underrepresented in the selected KM journals.

Figure 8 represents the popularity of KM research methods in the selected sample. Primarily, qualitative studies used interviews as the primary instrument of data collection. Focus group discussions, observations, and document analysis are also used as data collection methods in qualitative studies. In quantitative studies, questionnaire is the main instrument of data collection, particularly in survey designs. As shown in Fig. 8, interviews are the most prevalent data collection methods followed by questionnaire method. Observations, focus groups and document analysis are less prevalent than interviews and questionnaire in KM studies. This tendency is in line with the study of Fteimi and Lehner [13] in which interviews and questionnaires are among the most frequent research methods compared to other methods.

Table 3 Framework validation

Article	Technological dimension	Business dimension	People dimension	Domain/application dimension
Attia and Salama [75]		✓		✓
Hussinki et al. [77]		✓		
Barão et al. [78]	✓			✓
Gupta and Chopra [79]		✓		✓
Torres et al. [80]		✓	✓	
Abualoush et al. [81]			✓	
Durst and Pietro [82]		✓		✓
Tsang et al. [83]	✓			✓
Lejla and Nijaz [84]		✓		✓
Hwang et al. [85]		✓	✓	
Daňa et al. [86]		✓		✓

5 Evaluation

This section evaluates the results obtained from this study. According to Myers [46], the evaluation criteria concern the validity and the generalizability of the result. For validity, this research applied text mining technique to extract the initial concepts from large amount of data. Extracting the concepts from large pool of data helps ensure the consistency and reliability of the results [39]. To validate the generalizability of the framework developed in Fig. 5, we followed the approach recommended by [29]. Particularly, we fitted new set of KM articles, which were not used in the framework building process. This approach validates the comprehensiveness of the developed framework [29]. The objective is to check whether the new KM articles fit the categories identified by LDA model and grounded theory. Basically, we used the abstracts of the new articles to achieve this objective. Particularly, abstracts of 11 KM articles, which were not used in the framework building process, were retrieved and analyzed to check if they fit the categories identified by grounded theory and topic modeling.

As shown in Table 3, all 11 articles were successfully categorized under the framework dimensions. Five articles were grouped under business and domain/application dimensions, two articles were grouped under technological and domain/application dimensions, two articles were grouped under business and people dimensions, one article is classified under people dimension, and one under business dimension.

To illustrate the process of articles classification, take the article "Knowledge management capability and supply chain management practices in the Saudi food industry" by Attia and Salama [75] as an example. The abstract of this articles is:

> Purpose: The purpose of this paper is to examine the effect of knowledge management capabilities (KMCs) on supply chain management practices (SCMP) and organizational performance (OP) in firms, in addition to examining the effect of supply chain management on OP. Design/methodology/approach To demonstrate the effect of KMCs

on SCMP, and OP, different techniques such as factor analysis, correlation analysis, and structural equation modeling were used to verify the validity of the proposed conceptual model and to test the suggested hypotheses, using data collected from 165 companies in the Saudi food industry (representing a response rate of 74.9 percent). Findings According to the study's findings, SCMP are positively affected by KMCs. Moreover, OP is directly affected by KMCs and SCMP. Research limitations/implications Due to the specific nature of the sample, the findings of the current research are applicable only to the food industry. Originality/value. The current research introduced a conceptual model, which has been tested and verified in the Saudi food industry. The findings recommend that both KMCs as well as SCMP will contribute to improving the OP. In addition, KMCs will improve the SCMP.

The main contribution of this paper is to propose a conceptual model to examine the impact of KM capabilities on supply chain management and organizational performance. Therefore, it can be grouped under business dimension. Moreover, the study tested the proposed conceptual model in Saudi food industry. Therefore, this article can also be grouped under application/domain dimension.

Successfully categorizing existing KM articles using the framework verifies its comprehensiveness.

6 Conclusion

This research aims to identify the current research themes in KM field. It also presented a descriptive framework for the field. To achieve this end, a large corpus of KM-related articles was collected and analyzed using text mining and grounded theory approaches. The framework includes four core categories concerning technology, business, people, and domain/application dimensions. The results show a strong interest of researchers in different knowledge management-related topics. Among others, business dimension-related themes like knowledge types, knowledge processes, managerial issues, intellectual capital, and innovation are frequently investigated areas of research. Notable is also a remarkable number of research papers deal with KM technologies-related topics. The descriptive framework provides a consolidated view of overall research topics in KM. The framework was evaluated by fitting a new set of KM articles to the framework to see if it successfully classified the articles according to its categories.

This study also has implications for research methodologies in the selected KM journals. The results obtained about the research approaches and methods deployed in the selected KM studies raise the awareness about the most favored research methodologies in this field and provide directions for future deployment of research methods and approaches.

This study has many contributions. Methodologically, it shows the applicability of using text mining (topic modeling) with grounded theory approach to automatically extract the initial concepts from a large amount of data. It also founded its procedure on a well-accepted theory (grounded theory) and built its procedures and conclusions on a large set of existing published research.

Theoretically, the framework developed in this study contributes to the theoretical foundation of KM field. It provides a comprehensive view of this field and points out to the areas of KM research. The strength of the framework and the process of concluding to the KM dimensions derives from the reputation of KM journals selected and the comprehensive sample of text used. The study utilized all articles published in the last 20 years and within six reputable journals.

Practically, the results obtained from this study provide practitioners with a useful quality reference source. The topics included in this research pinpoint the interest in certain areas that are not well researched and provide a guide for future work. The framework and the components included provide researchers, practitioners, and educators with an ontology of KM topics, where they can cover deficiencies in research and provide an agenda for future research.

This study is not without limitations. First, this study is limited by the selection of sample journals. The sample was mainly from the top-ranked KM publications. Conferences papers, KM books, and other refereed journals were not included in the analysis. Therefore, the descriptive framework might not reflect the topics of conferences papers, KM books, and refereed journals articles related to KM. The second limitation is related to the results obtained from employing topic modeling algorithm. Although topic modeling is effective in finding underlying topics in documents, the user trust in the discovered topics is still an issue [76]. Therefore, further investigation of the evaluation methods for topic modeling is recommended to further trust the topics discovered by employing this unsupervised technique.

Third, due to the large number of the selected KM publications, the analysis of the used research methodologies was limited to automated word frequency count method. Future research can extend the analysis by employing manual coding schema to provide a complete picture of the analysis. For example, reporting analysis on the use of qualitative and quantitative case studies and the triangulation of the research methods and research designs.

Fourth, this study used the title, abstract, and keywords to discover the major research trends in KM field and reveal the research methodologies deployed in selected KM studies. However, in some cases the title, abstract, and keywords do not catch all the content of the paper. Therefore, future research can extend the current study by employing full text analysis.

Appendix A

See Table 4.

Table 4 KM concepts

Topic	Concept 1	Concept 2	Concept 3	Concept 4	Concept 5	Concept 6	Concept 7	Concept 8	Concept 9	Concept 10
From 1997 to 2003										
Performance measurement	KM	Performance	Measures	Government	KMS	Organization	Scorecard	Balanced	Capital	Transfer
Intellectual capital	Intellectual	Capital	Knowledge	Learning	Management	Value	Asset	Organizational	Strategy	Performance
Organizational learning	Learning	Sharing	Organization	KM	Organizational	Culture	Case	Communities	Infrastructure	Results
Information technology	Information	Learning	Process	Development	Communities	Transfer	New	Approach	Technology	Systems
Knowledge management systems	Information	KM	Data	Systems	Organizational	Discipline	Tacit	Organization	Competitive	Advantage
Innovation	Theory	Organizational	Learning	Model	Process	Innovation	Transfer	Based	Systems	Practice
Knowledge workers	KM	Organization	Human	Public	Organizational	Capital	Creativity	Dynamic	Strategy	Sector
Knowledge economy	Culture	Cross	Cultural	Worker	Economy	Technology	Business	Technologies	Process	Information
KM processes	KM	Business	Innovation	Organizational	Managers	Processes	Study	Divide	Systems	Activities
Tacit and explicit knowledge	Capital	Tacit	Learning	KM	Intellectual	Information	Technology	Organizational	Explicit	Human
From 2004 to 2010										
Knowledge discovery	Mining	ERP	Association	Military	EKO	Rule	Frequent	Closed	Rules	Revolution
Knowledge city	Cities	Local	Wikis	Discovery	Tags	Scenario	Transfer	Wiki	Urban	Learning
KM barriers	Sharing	Virtual	COPs	Barriers	Urban	Online	Cities	List	Distributed	European
Promote KM program	KM	Transfer	Motivation	Cities	Alliances	Autopoiesis	Generation	Collaboration	Scientific	Rewards
Community of practice	COPs	Virtual	COP	NPD	Dispersed	Teams	Ontology	Communities	MNCs	Work

Table 4 continued

Topic	Concept 1	Concept 2	Concept 3	Concept 4	Concept 5	Concept 6	Concept 7	Concept 8	Concept 9	Concept 10
KM tools	Metaphors	Mobile	Exploration	Leadership	MKS	Competence	Polanyi	Videoconferencing	Mining	Snowden
Readiness	Enterprise	Metaphor	KT	Game	Readiness	Heterogeneity	Procurement	Discourses	Epistemology	Metaphors
Organizational learning	KM	Sharing	Organizational	Study	Capital	Based	Transfer	Process	Learning	Information
Industry	Transformational	Video	Older	Film	Healthcare	Hospital	Polanyi	Secondary	Bangkok	Tourism
Ontology	Capital	Intellectual	IC	Assets	Explicit	Sustainable	Framework	Models	Capacity	Ontology
From 2011 to 2018										
Knowledge engineering	KSBs	Readiness	Planning	Spillovers	Engineering	Ontology	Territoriality	Codification	School	Gas
Subsidiary knowledge	Green	Subsidiary	Subsidiaries	Artifact	Teams	BI	Learning	Sharing	Engineering	Intentions
Analytics	Ontology	NPOS	Analytics	Web	Semantic	Ontologies	Sites	Search	Readiness	Phishing
Big data	KS	PKM	KT	Big	Learning	Management	Enterprise	Information	Entrepreneurship	Memory
Innovation	KM	Management	Sharing	Capital	Innovation	Study	Research	Performance	Organizational	Paper
KM visualization	NPD	Banks	Visualization	Codification	Prototyping	Affection	Sourcing	Transactive	Patterns	District
Personal knowledge	Tacit	Team	Trust	KIBs	Cultural	Subsidiary	Teams	PKM	Competences	Exploitation
Online knowledge sharing	KS	Students	KSBs	Behavior	Online	Face	Barriers	Contingency	Attitude	Directions
Data mining	IC	Ontology	Mining	Classification	Family	KSBs	SC	Ontologies	Engineering	Fuzzy
Knowledge marketing	Retention	KM	CKM	Face	Flows	Hospital	School	Sharing	Brazilian	Stocks

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