Exploring the topic structure and evolution of associations in Information behavior research through co-word analysis

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Abstract
This study aims to reveal the distribution of topics and associations among them in information behavior research from 2009 to 2018. Working with a collection of 6744 publications from the Web of Science database, co-word analysis is used to investigate the topic structure, associations among topics and their evolution in different years, with the supplement of visualization of science map. Results uncovered an unbalanced distribution of topics, and topics cluster into six communities representing subdivisions of this field, including information behavior in patient-centered studies, information interaction in digital environment, information literacy in health and academic context, health literacy on the Internet, information behavior in child-centered studies and information behavior in medical informatics. Findings supplement and provide refinements to work on the state of this field, and help researchers obtain an overview in the past decade to guide their future work.
Keywords
Information behavior research, co-word analysis, topic structure, topic evolution

Introduction

Information behavior can be defined as “the totality of human behavior in relation to sources and channel of information, including both active and passive information seeking, and information use” (Wilson 2000, p. 49). With origins in library science and philology research, Information behavior research can be traced back to the 1920s (Lu, 2012). Since then, it has developed into a core subdivision in library and information science (Julien *et al.*, 2011). In the past few years, we have witnessed the rise in popularity of various information technologies, such as the Web, social media, smartphones, etc. Information technology’s development provides diverse information channels and resources to users. For instance, the growing penetration of social media has changed patterns of information behavior fundamentally (Acquisti *et al.*, 2015). Besides, emerging issues such as user privacy and information security widely exist in problematic information practices (Chen *et al*., 2013; Wang *et al*., 2018). Consequently, studies in this field has dramatically increased.

Given (2012) notes that, synthesis of publications in a specific discipline could help us gain a comprehensive overview of that field. In this vein, several studies have been conducted to scrutinize the status of information behavior research (e.g., Vakkari, 2008 or Greifeneder, 2014). Nonetheless, there is a dearth of knowledge of the overall topic structure, associations and their evolution in this field. Topic structure will identify prominent themes and their associations. On the basis of dynamic evolution analysis of associations among topics, trajectory or trends in this field could be demonstrated (Muñoz-Leiva *et al*., 2012; Wang *et al*., 2012; Tang and Zhang, 2015). In order to fill the gap of previous studies, we endeavor to investigate the hotspots and trends in information behavior research.

The body of the paper is organized thus: A literature review is presented in the next section, including a brief summary of the state of and topics in information behavior research, and the rationale for our study. After that, we introduce the research methodology applied, including the data collection, data processing, and the data analysis employed. Then, we outline the results obtained from the data analysis and elaborate on the findings. We conclude the paper by highlighting the implications of this research. Limitations are clarified and suggestions are given for future research.

Literature Review

The state of information behavior research

Information behavior studies has been growing steadily in recent years. Worthy of special note are a few studies that have traced the development mainly from the angles of quantity, approaches (Vakkari, 2008; Julien *et al*., 2011; Greifeneder, 2014), authors (González-Teruel *et al*., 2015; Julien *et al*., 2011), topics (Vakkari, 2008; Greifeneder, 2014), and interdisciplinarity (Julien *et al*., 2011; Given *et al*., 2012). These studies elucidate that theoretical studies in the field are scarce and generally fail to make a breakthrough in terms of theories and models (Vakkari, 2008). In addition, methods used in information behavior research have been constantly enriched. Apart from well-known approaches such as log file analysis and eye-tracking, participatory designs such as shadowing, narrative studies, cultural exploration, and geographical analysis techniques raise more concern in this field (Greifeneder, 2014).

Some important features were found pertaining to the field. For instance, compared to quantitative analysis, qualitative methods still dominate in information behavior (Vakkari, 2008; Greifeneder, 2014). Methods such as interviews, surveys, and diary-based observation are widely used to investigate differences of information behavior patterns among different groups (Julien *et al*., 2011). In addition, researchers with a background in academia make substantial contributions and consist of the core research force (González-Teruel *et al*., 2015). A few scholars endeavored to reveal the topics of this field, such as information needs, information retrieval, and information-seeking (Vakkari, 2008; Greifeneder, 2014; Eungi, 2017; Shen *et al*., 2017). Interdisciplinary research is also notable in this field (Julien *et al*., 2011; Eungi, 2017). Insights obtained from work on medicine, information systems, computer science and social sciences contribute to new foundations, and the field is supplemented by knowledge from other disciplines: economics, management, and the humanities.

Topics of information behavior research

The foci of information behavior research varies in various periods. By analysis of ISIC conference papers published from 1996 to 2008, Vakkari (2008) found that most studies centered on information behavior of professionals, online information behavior, and information search behavior. Research on the last of these focused mainly on efficiency of information behavior in everyday life, while work on online information behavior such as web searching became slightly more common. Before 2012, alongside information behavior in day-to-day life, topics such as user experience, information needs, and information seeking received great attention as well (Han, 2013). Lin (2014) also states that lots of topics refer to various information behavior models, such as Wilson's Information Behavior Model (Wilson, 2008), Dervin's Sense-Making Model (Dervin and Nilan, 1986), and Ellis's Information Search Model (Ellis, 2011).

Reviewing papers published in 2013–2014, Greifeneder (2014) took this work further and divided the field into three subfields: information interaction (e.g., information sharing and information management), information behavior of special groups (e.g., people in the health sector or marginalized groups), and information behavior in context (e.g., social media or digital environments). The results showed that, even though studies on information seeking and information needs still dominated the field, several new topics had emerged, such as information sharing and information-related practices (e.g., Pilerot, 2013).

Rather than confine themselves within limited groups, some researchers set out to study information behavior among minority or marginal groups such as pregnant women (e.g., Laferriere and Crighton, 2017) and immigrants (e.g., Lloyd *et al*., 2013). Alongside such work, numerous researchers conducted relevant work in context of natural environment, including homes (e.g., Foss *et al*., 2013) and workplace (e.g., Hassan Ibrahim and Allen, 2012).The number of information behavior research in field of health and medicine increased particularly strongly in the time span researched (Kim and Syn, 2014; Eungi, 2017). Besides, online information behavior is also identified as an important topic in this field, and related studies have increased over years (Eungi, 2017), which can be attributed to the broadband penetration of Internet since the 21st century (Buente and Robbin, 2008).

The above discussion provides evidence from the literature that topics of this field are various and evolve over time. In this process, new topics are emerging and knowledge outside this discipline have been borrowed or integrated into this field.

For methods used in previous work, quantitative research methods such as social network analysis and bibliometric method are common. Keyword analysis is one of the main bibliometric tools applied to reveal hotspots, because keywords are proxies of the core content and sometimes reflect the emerging topics. However, the descriptive statistic of keywords is not enough for understanding the state of information behavior research. Keywords with similar features could cluster into a community, which can be regarded as a subfield. Thus, co-word analysis is also used in several studies in order to further detect topic clusters, which represent various subfields of information behavior research and reveal the distribution of hotspots (e.g., Han, 2013). Besides, other researchers draw on content analysis to analyze the topics of this field (e.g., Vakkari, 2008). They collected related literature from conferences or journals and provide an overview of topics in this field.

In addition to the analysis of topics, other studies also analyze the status of information behavior research in terms of co-citation and co-authorship. Unlike work using co-word analysis, these studies mainly explored the knowledge base or collaborations among authors in this field. For instance, on the basis of co-citation of references, McKechnie *et al*., (2005) identified some important articles published between 1993 and 2000 in this field. Other researchers also drew on co-authorship analysis to identify the most prominent authors and their collaborations in this field (Li-Ping, 2009; Chang, 2011; González-Teruel *et al*., 2015).

The rationale for the study

Emerging information technologies in recent years, such as the social media, smartphones, wearable devices, etc., provide lots of information channels and resources, which alters patterns of human information behavior and information activities. Thus, numerous work in this field studies various issues of this field and the number of it has significantly increased (Hu *et al*., 2015). However, prior studies are limited to analyzing the topics of information behavior research nearly 2010. Few studies trace the changes or trends in the past decade. When reviewing previous studies, we found that most studies drew on a data-sample timeframe of at least ten years (e.g., Julien *et al*., 2011). Hence, we provide an overview of topics in this field from 2009 to 2018.

When exploring topics of information behavior literature, previous studies mainly described the topics and further classified them into different communities, drawing on keyword analysis or other methods. Even though some studies used co-word analysis, they ignored the strengths of associations among these topics. With the aid of the strengths and numbers of associations, a topic-network could be detected into various sub-communities in details, along with the density and centrality of these sub-communities (Ding *et al*., 2001). This facilitates in-depth analysis of status or trends of topics and subfields in information behavior. Thus, in this study co-word analysis will be used to reveal the topic structure, the corresponding sub-communities and their status in this field.

Albeit we could trace current trends of topics in information behavior research by analysis of literature in different periods, year-specific visualization of topics and their associations is more systematic and concrete. The emergence or extinction of topics, split or merger of their associations can be intuitively observed in a longitudinal evolution process. Therefore, in order to gain an overview of evolution of topics and their associations from 2009 to 2018, a longitudinal science map will be used.

Methodology

Collection and processing of the data

The research dataset was collected from Web of Science (WOS) publication collections. We searched for relevant publications as the data sample via using “information behavior” and terms representing a wide perspective of information behavior research, following the widely accepted Wilson’s Information Behavior Model. This model contains comprehensive dimensions of user’s information behavior, including user interaction with information, information systems and information retrieval systems (Wilson, 1999). Previous studies also used similar search strategies and terms (Julien *et al*., 2011; Hu *et al.*, 2013; González-Teruel *et al*., 2015; Eungi, 2017; Shen *et al*., 2017), we discriminated their relevance and selected expressions similar to information behavior in our search strategy in order to minimize the incidence of false negatives (the omission of relevant publications).The search strategy of this study is as follows:

TS=("information behavio*") OR TS=("information seek* behavio*") OR TS=("information search* behavio*") OR TS=("information practice*") OR TS=("information encounter*") OR TS=("information shar* behavio*") OR TS=("information needs") OR TS=("information use behavio*") OR TS=("information exchang* behavio*")

Considering the different spellings (e.g., “behavior” or “behaviour”) or various forms of words (e.g., “search” and “searching”), the truncation retrieval technology (marked as an asterisk) preventing the omission of related publications was applied in order to keep the quality of publication retrieval. The time span for publication retrieval was from year 2009 to year 2018, and the publication types included “Article,” “Proceedings Paper,” and “Review”. Then we screened the retrieved publications. All these publications were checked for elimination of duplication, and 6744 publications were ultimately retained for data analysis, including 4692 articles, 1725 proceeding papers and 327 reviews from 1928 journals and 60 proceedings. These publications included 16762 keywords and their total frequency is 32807.

Furthermore, we standardized the keywords from the author-provided ones reported in these publications. All synonyms were merged into the specific one (e.g., "information seeking" and "information seeking-behavior" were replaced by "information seeking behavior"). In line with past studies (e.g., Shen *et al*., 2017), 27 general terms (total frequency is 784) used in a broad sense or vague ones such as "innovation", "review", "analysis", "development", "influence" and "research" were excluded. In particular, since our research focused on information behaviors, 37 search term (total frequency is 1765) such as "information behavior", "information practice" and 15 synonyms (total frequency is 152) such as "user behavior", "human information behavior" were excluded as this study aims to explore from what aspects of studies of information behavior focus on (e.g., Shen *et al*., 2017). Hence, in all, 16683 keywords representing the corresponding publications were retained for analysis. The frequency of these keywords is 30106 times. As shown in Table 1, with the growth of publications every year, the keywords contained in publications are growing, and the word frequency is also growing over years.

Table 1. Description of keywords in each year

Year	Publications	Keywords	Frequency
2009	422	1495	1817
2010	436	1607	1890
2011	472	1717	2099
2012	507	1809	2241
2013	616	2159	2731
2014	617	2169	2713
2015	872	3003	3898
2016	975	3344	4368
2017	909	3238	4098
2018	918	3204	4251
Total	6744	23745	30106

Then the keywords with high frequency were extracted as the base for our analysis, because keywords of this nature usually represent the research hotspots. We used the equation proposed by Donohue (Rosenberg, 1973), which distinguishes between high-frequency words and low-frequency words as follows:

$$T = \frac{-1 + \sqrt{1 + 8I}}{2}$$

Here, I represents the frequency of all these 16683 keywords. On this basis, keywords appearing at least 10 times were retained for analysis to represent the research topics. These keywords appear, in total, 6647 times in the corpus, accounting for nearly 22% of all keywords. Therefore, these 246 keywords are representative of the major topics in this field.

Methods and tools

Co-word analysis, as adopted in this study, maps the knowledge network to illustrate how ideas and concepts interact within a given scientific field (Small and Griffith, 1974; Coulter *et al*., 1998). In this approach, keywords, serving as a proxy for terms representing publications in that field, are assumed to reflect a specific scientific topic, and the association strengths of terms may reveal the trends in the relevant discipline (Ding *et al*., 2001; Liu *et al*., 2012; Liu *et al*., 2016). Accordingly, a time-series record of changes in the concept networks could also trace the development of the field, drawing on visualization of intellectual structure (Grauwin and Jensen, 2011; Hu *et al*., 2011; Hu *et al*., 2018). Specifically, a node in a co-word network is a keyword representative of pertinent literature, while a link connecting two nodes reflects the co-occurrence of two keywords. The strength of associations between those keywords represents the frequency of co-occurrence, while the size of a node indicates the centrality of the associated topic. Though this approach displays such disadvantages as subjectivity in the assignment of keywords (Lu and Wolfram, 2012), the unique features through which one can reveal the conceptual space and interactions of key terms are in accordance with our purpose of uncovering the topic structure and their associations in the information behavior field (Clarke, 2008).

Certain indicators in network analysis can be used to identify the structure and pattern of co-word networks via calculation of the internal or external cohesion of a specific co-word network, including density, centrality, centralization and clustering coefficient. Density, an indicator of internal cohesion, refers to the strength of internal links among keywords across the whole network (Callon *et al*., 1991; He, 1999), thereby measuring both how the relevant field maintains itself and the maturity of that field (Viedma-del-Jesus *et al*., 2011; Muñoz-Leiva *et al*., 2012). Clustering coefficient is another important cohesion indicator, demonstrating how the network is clustered. A high clustering coefficient indicates that the nodes in the network have a greater chance of being linked with each other. Among the indicators of external cohesion are centrality, which address the intensity of connections between sub-networks in the conceptual network (Callon *et al*., 1991; Hu and Zhang, 2017). Those sub-networks with stronger external cohesion represent the emphasis of attention from the scientific community (Nielsen and Thomsen, 2011). Three important centrality measurements are degree centrality, closeness centrality, and betweenness centrality. The first describes the number of direct associations of a node with other nodes in the network (Rogers, 1974). Closeness centrality, in turn, refers to the geodesic distance of a node to all other nodes in the network (Rogers, 1974). Betweenness centrality is the frequency of a node that falls between pairs of other nodes (Freeman, 1977). A node with high betweenness centrality plays a bridging role, connecting subgroups in the network (Freeman, 1977; Hu *et al*., 2018). Different from the micro-level description on centrality of one node, degree centralization, closeness centralization and betweenness centralization measure the centrality of the global network, which means the central tendency of the whole network to several dominant vertexes (Beauchamp, 1965; Freeman, 1978).

Sci2, a powerful software tool for network analysis, was used to conduct statistical analysis and visualization (Börner, 2011). Firstly, we imported standardized bibliographic data into Sci2 after deleting duplication and normalizing, then generated a co-word network. From the network setup, we calculated network indicators via the Pajek software, which was developed for social-network analysis (Doreian *et al*., 2013). After this, the Louvain community-detection algorithm of Pajek was employed to divide the co-word network into sub-communities that represent subfields of information behavior research (Blondel, 2008; Leydesdorff *et al*., 2014). The community-discovery algorithm has a strong advantage in its breakdown of theme community: it can display many knowledge areas and structural details in the network. VOSviewer was then applied for optimizing the visualization of these sub-communities (Eck and Waltman, 2010). Furthermore, for the analysis of associations among topics in different periods, we employed CorText to analyze the evolution of interactions among topics in information behavior research (Rosvall and Bergstrom, 2010; Leydesdorff and Goldstone, 2014).

Results

The distribution of topics in information behavior research

The top 50 keywords are presented in Table 2 in a descending order of prevalence. These topics can be regarded as hotspots in the field for their high occurrence. “Internet” ranks top one in this field, since this topic has the highest occurrence. It is followed by “information needs”, ”information retrieval”, “Internet”, “cancer”, “communication”, “breast cancer”, “cancer”, “communication”, “decision making” and various other topics. The top 50 topics cover abundant fields, such as different kinds of information behaviors (e.g., “health information seeking”, “health information needs”, “information management”), contexts (e.g., “Internet”, “social media”, “academic libraries”, “health information”), research methods (e.g., “qualitative research”, “focus groups”, “questionnaire”), groups (e.g., “students”, “nurses”, “child”, “caregivers”) and so forth. Studies of information behavior inevitably deal with context, but it is noticeable that there are lots of topics related to the context of health and medicine: “cancer”, “health literacy”, “consumer health information”, “patient information”, etc. In addition, compared to quantitative research, topics of qualitative research such as that termed “qualitative research” have high occurrences in current studies. These prominent topics in Table 2 elucidate main aspects of information behavior research in the last ten years.

Table 2. Distribution of topics in information behavior research (Top 50 topics)

Rank	Theme	Frequency	Rank	Theme	Frequency
1	Internet	211	26	palliative care	48
2	cancer	203	27	questionnaire	46
3	communication	177	28	shared decision making	46
4	decision making	166	29	patients	45
5	qualitative research	137	30	query expansion	45
6	breast cancer	135	31	survivorship	44
7	information literacy	122	32	focus groups	44
8	social media	117	33	health communication	43
9	oncology	95	34	information services	42
10	patient education	95	35	knowledge management	41
11	health literacy	87	36	information systems	40
12	consumer health information	76	37	students	38
13	health information	74	38	library	38
14	information sources	71	39	data mining	38
15	child	70	40	e-health	37
16	ontology	64	41	prostate cancer	37
17	parent	64	42	health information seeking	37
18	information management	64	43	evidence-based practice	37
19	nursing	57	44	patient information	37
20	social networks	56	45	privacy	37
21	search engines	54	46	health information needs	36
22	academic libraries	53	47	pregnancy	36
23	qualitative methods	52	48	anxiety	34
24	adolescents	50	49	nurses	34
25	electronic health records	49	50	caregivers	33

Characteristics of topic networks of information behavior research

Based on the all 246 keywords, a co-word network for the topics was generated. Table 3 shows the attributes of the co-word network, which consists of 246 nodes and 2610 links. The values for the network indicators calculated via Pajek are presented in Table 3. The values for network density (0.0866) and clustering coefficient (0.2712) are low, showing the existence of loose relationships among various topics, but the closeness centralization (0.3741) of the network is relatively high, indicating that most of topics are directly linked and interaction between these topics is ubiquitous. The level of degree centralization (0.3983) is relatively high, showing that some topics have become dominant in information behavior research and are also closely associated with other topics in the network. These dominant topics would be discussed afterwards. The value of betweenness centralization (0.0889) reveals that few topics with relatively high betweenness centrality play the “bridge” role and associate with most other topics in the topic network. Except these topics, a large numbers of the other topics are scattered to the peripheral in the network.

Table 3. Indicators for the topic network

Indicator	Value
number of nodes	246
number of links	2610
average degree	21.2195
degree centralization	0.3983
closeness centralization	0.3741
betweenness centralization	0.0889
clustering coefficient	0.2678
density	0.0866

Since a small set of topics has the dominant position in the co-word network, these topics (the top 10 by ranking) were selected for further analysis with regard to occurrence, degree centrality, and betweenness centrality. Table 4 presents the top 10 topics in terms of occurrence, degree centrality and between centrality. With the exception of the topics referred to as “breast cancer”, “information literacy”, etc., every one of them is in the top 10 for all three attributes. The topics with high frequencies reflect the hotspots of this field, while topics with high degree-centrality values present their dominant position in this field. A higher degree of betweenness indicates a stronger “bridge” effect in linking other topics. As is visible from Table 4, “Internet”, “cancer”, communication”, “decision making”, “qualitative research”, “social media” and “patient education” consist of the dominant topics across the three attributes, indicating their core position in the field and link other scattered topics into a topic network. The reasons why these topics become the dominant will be analyzed in detail later in conjunction with specific research areas.

Table 4. Top 10 topics in terms of occurrence frequency, degree and betweenness centrality

Rank	Topic	Occurrence frequency	Topic	Degree centrality	Topic	Betweenness centrality
1	Internet	211	Internet	118	Internet	0.0934
2	Cancer	203	Cancer	95	Decision making	0.0696
3	Communication	177	Decision making	88	Social media	0.0633

4	Decision making	166	Communication	85	Communication	0.0484
5	Qualitative research	137	Qualitative research	82	Qualitative research	0.0430
6	Breast cancer	135	Health literacy	70	Cancer	0.0390
7	Information literacy	122	Social media	69	Health literacy	0.0299
8	Social media	117	Patient education	69	Consumer health information	0.0288
9	Oncology	95	Consumer health information	66	Information literacy	0.0278
10	Patient education	95	Breast cancer	66	Patient education	0.0260

On the basis of the features of associations among the topics in the network, the network is detected into six sub-communities (see Figure 1), which named after their dominant and major topics: information behavior in patient-centered studies (denoted as C1), information interaction in digital environment (C2), information literacy education research (C3), health information literacy on the Internet (C4), information behavior in minor-centered studies (C5) and information behavior of electronic health user (C6).

Table 5 shows the global network characteristics of these six communities. The density and clustering coefficient of all sub-communities are higher than the corresponding indicator of the global network, indicating the sub-community has strong internal associations and represents a subfield. As shown in Table 5 and Figure 1, topics in C1, C2, C3 and C4 tend to associate with neighboring topics, of which the number is more than mutual associations among different communities. This is because topics within the same field have more connections because of similarities in essence than external connections with other fields. Communities of C1 and C4 have the largest number of mutual associations, for one of the groups of health information literacy research is patients. As a community of specific groups, C6 is not an independent subfield of information behavior research. Minors are also an integral part of the patients and the target group of health information literacy education, so C6 has many associations with information behavior of patient (C1) or health information literacy (C4). Likewise, as a subdivision of medical informatics, information behavior of electronic health user naturally associate with studies of information behavior of patient (C1) or health literacy research (C4). In contrast, C2 has fewer links (47, 130, 147, 24 and 38 links with C1, C3, C4, C5 and C6 respectively) with other communities and mostly collaborates with topics within itself (311 links). This is because compared to topics in other communities, topics in C2 are more overlapping in nature, focusing on the analysis methods, technology and context. Except for C2, the centralization indicators of other communities are relatively high, indicating that these communities tend to concentrate on several dominant topics and homogeneous topics tend to associate with them to form evident subfields. It may be that components in C2 are complex and consist of relatively heterogeneous topics such as analysis methods, emerging technologies and scenarios. This is consistent with the distribution of associations among these communities aforementioned.

Table 5. Associations and network indicators of six sub-communities

Community	Links between or within the communities						Degree centralization	Closeness centralization	Betweenness centralization	Density	Clustering coefficient
	C1	C2	C3	C4	C5	C6					
C1	*1068*	47	268	412	176	89	0.6675	0.6947	0.1598	0.2761	0.4074
C2	47	*341*	130	147	24	38	0.3588	0.3762	0.1446	0.1359	0.2906
C3	268	130	*383*	249	47	76	0.4499	0.4371	0.1493	0.2143	0.4062
C4	412	147	249	*421*	95	60	0.5935	0.5908	0.2341	0.2436	0.4009
C5	176	24	47	95	*96*	10	0.5429	0.5985	0.3116	0.3250	0.4550
C6	89	38	76	69	10	*82*	0.4211	0.4255	0.2110	0.3053	0.3866
Global network							0.3983	0.3741	0.0889	0.0866	0.2678

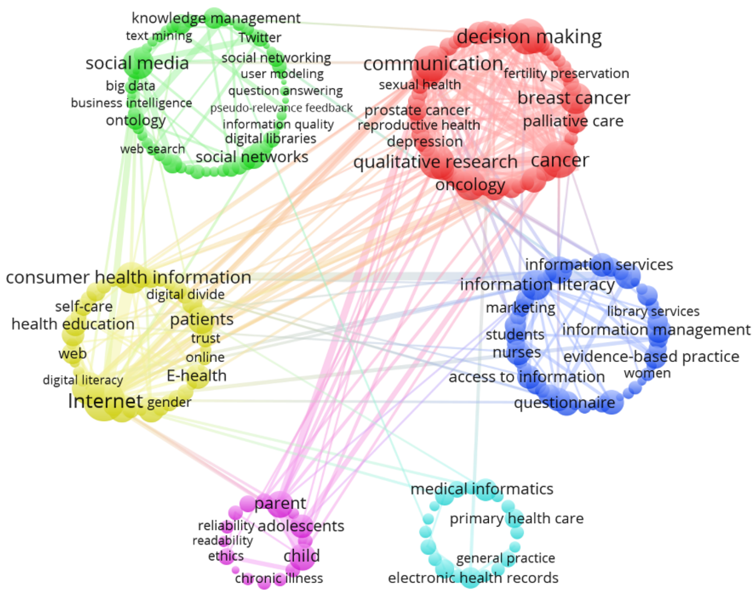

Figure 1. The co-word network of information behavior research (from the top 10% links)

Information behavior in patient-centered studies

C1 shows information behavior research pertaining to patients, which is the largest one in all six sub-communities as shown in Table 5. The reason may be that health information needs and related behaviors are widespread in various groups, regardless of the differences in occupations, ages, educational levels, etc. People obtain health information based on their health status for prevention of disease, health maintenance, and medical diagnosis. Bundorf's (2006) investigation found that 94% of patients reported health information needs for at least one disease, resulting in large amounts of information behaviors related to health and medicine. The need for health information includes not only individuals with specific health conditions, but also people who are concerned about public health issues as shown in Figure 2. Meanwhile, the Internet also changed the way people find health information, from passive information received from mass media or professionals to active information sought through Web (Wong and Cheung, 2019), which triggers diverse information behaviors and needs of different people. Cancer and related topics are strongly central in C1. This is not only because of the increasing size of cancer patients, but also for the cancer patients' demand for health information is stronger than other patients (Finney et al., 2016). Qualitative methods seem to dominate this field, for its feasibility to reveal the information needs of users and explain the motivation or other psychological activities behind health information behaviors.

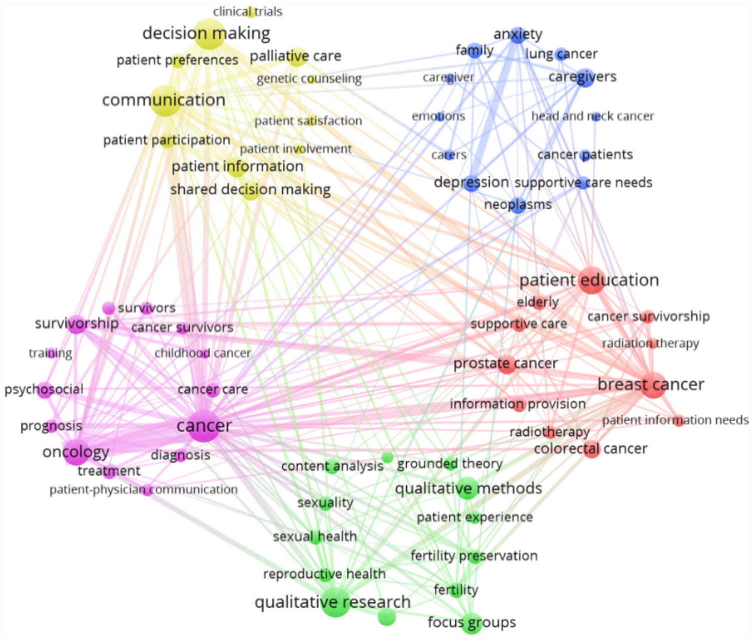

Figure 2. The network for C1 information behavior in patient-centered studies (from the top 50% links)

Information interaction in digital environment

C2 in Figure 3 discusses information interaction in digital environment, where most of topics are related to social media and emerging technologies. In the past decade, social media has been deeply integrated into people's daily lives. It gathers multiple information resources and is also the main channel for people to exchange information and show themselves (Hsieh, 2001), which provides a variety of behavioral samples for researchers, such as information creation, browsing, selection, interaction, evaluation and sharing. Information interaction of users in the digital environment also leave massive user-generated content in the network, which provides scenario and data guarantee for the application of emerging technologies such as big data shown in Figure 3. Meanwhile, mobile phones, smart wearable devices, etc. also provide material support for dynamic, real-time tracking and feedback of user behavior. Data processing and analysis technologies such as natural language processing and machine learning could process large amounts of unstructured user-generated content and predict user behavior preferences and trends.

Information literacy education research

Topics in C3 are related to information literacy research and mainly cover information skills, information resources and environments. Information literacy studies how people understand and judge when information is needed, and improve people's ability to obtain information, evaluate and effectively use information. The scope and content of this sub-community have more overlaps with human information behavior and has become an important subdivision in information behavior research. Although some topics shown in Figure 4 pertaining to health, most topics focuses on the field of education. The school, as a venue for teaching activities, is the main institution for cultivating information literacy. Library in school integrates a large number of information resources and tools, and thus plays an important role in information literacy education. This is the reason why there are lots of topics related to libraries and librarians in C3.

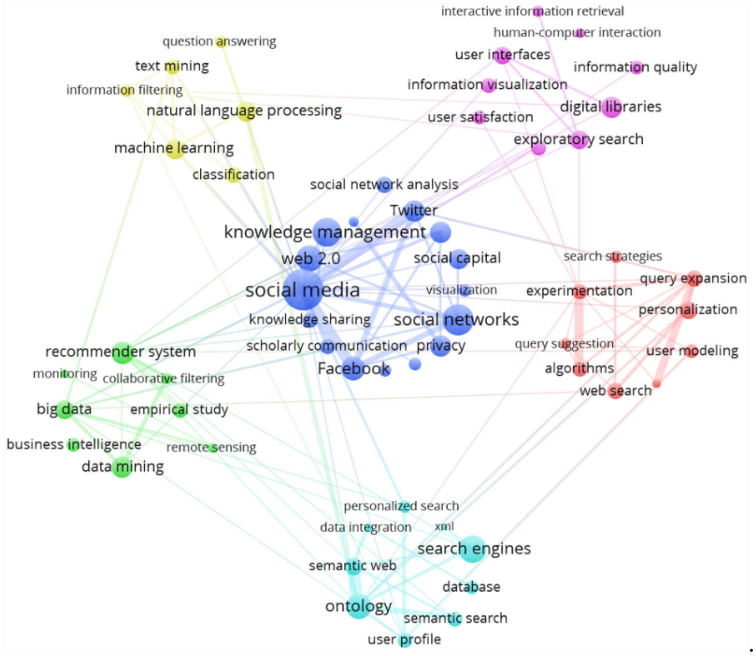

Figure 3. The network for C2 information interaction in digital environment (from the top 50% links)

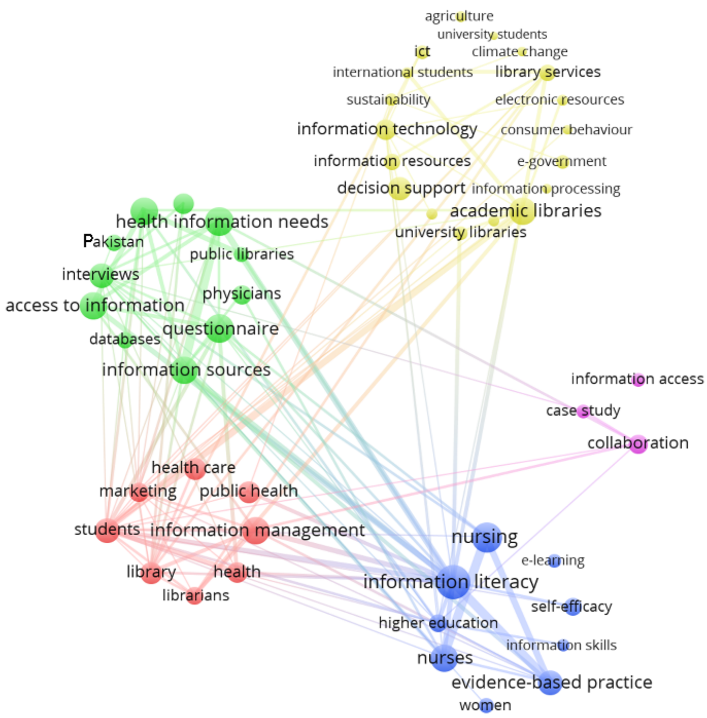

Figure 4. The network for C3 information literacy education research

Health information literacy on the Internet

Although the Internet has become an important way for people to obtain health information, there are still difficulties in the process of using the Internet, and even some elder patients have never used the

Internet to search for health information. Therefore, how to improve people's health information literacy also coincides with information behavior research as shown in Figure 5. As a branch of information literacy, health information literacy is an organic combination of health literacy and information literacy and was first proposed by the American Medical Library Association in 2003 (Juan et al., 2019). This sub-community involves different user groups, focusing on their ability to acquire and use health information. Besides, the topic “trust” shows that the quality and reliability of online health information has gradually attracted the attention of patients and researchers. The improvement of people's ability to identify the authenticity of health information will be another trend in this field.

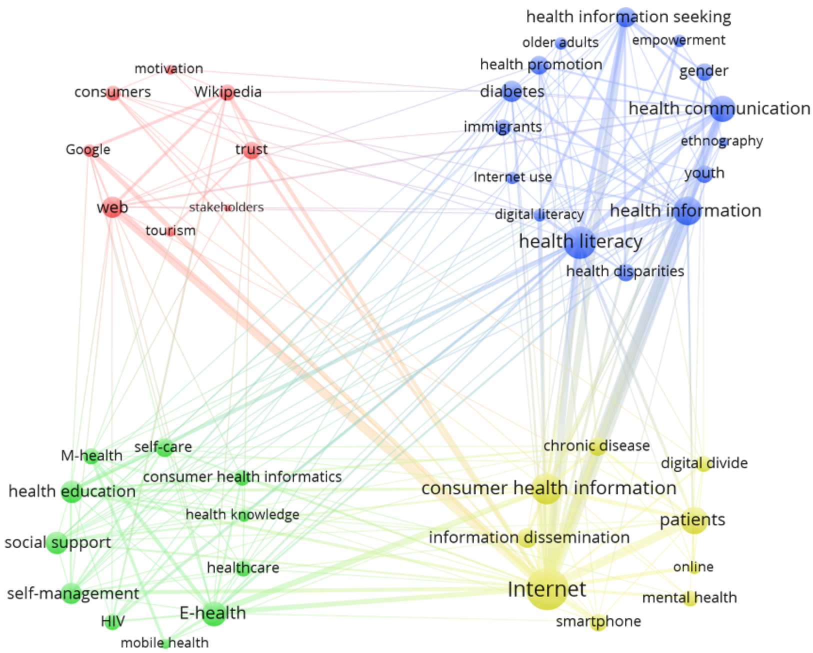

Figure 5. The network for C4 health information literacy on the Internet (from the top 50% links)

Information behavior in minor-centered studies

The range of groups in information behavior research continues to expand, and more researchers are turning their attention to special groups, such as the minor group in C5. This sub-community involves minor's information utilization and information ethics issues in the medical context. On the one hand, due to the limitation of cognitive ability and education level, children's information behavior is quite different from other groups, which requires more attention from researchers and practitioners. On the other hand, minors lack the necessary judgment and recognition ability for consequences of their actions, so more efforts should be paid to protect their personal information. As the guardian of minors, parents should have the right to know the handling of minors ’personal information, so as to ensure the safety of their information. So research related to minors couldn’t be separated from their guardians, which could explain why the topic of parent also have a higher degree of centrality in C4.

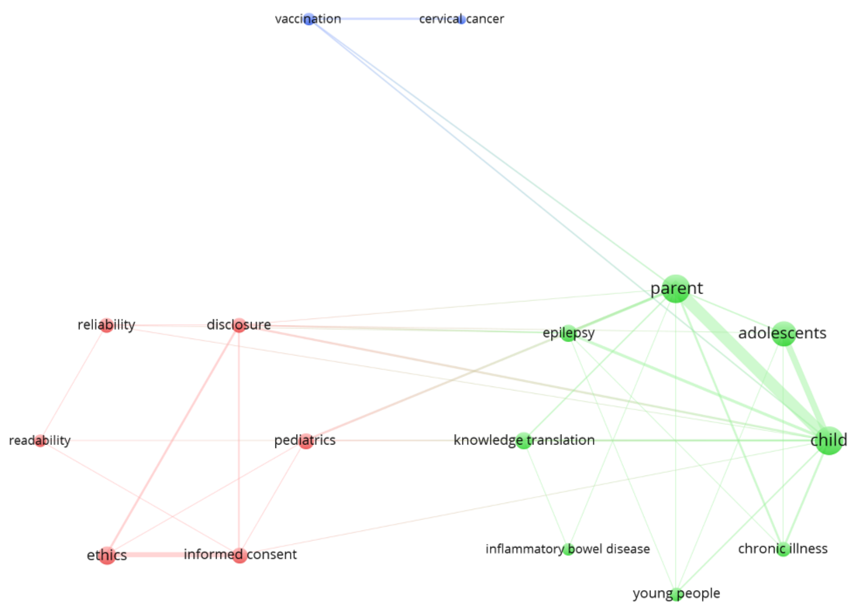

Figure 6. The network for C5 information behavior in minor-centered studies

Information behavior of electronic health user

The topics of technology, medical treatment and information in C6 are all related to electronic health records in Figure 7. With the rapid development of the Internet, information technology and mobile medical equipment have gradually become an emerging medical health information service. Electronic health record is widely used in disease prevention, health monitoring and online diagnosis and treatment. Electronic health record management system, wearable intelligent health equipment and mobile medical technology provide users with a more efficient and convenient way to obtain health information. The increasing users and the accompanying variety of information activities will inevitably produce various electronic health information behaviors of different groups, which becomes an important branch in information behavior research.

Figure 7. The network for C6 information behavior of electronic health user

The evolution of associations among topics in information behavior research

To trace the associations among topics in different years, we employed CorText to generate an evolution map. This map aids in visualizing details and structures of associations among topics based on flow-diagrams (also called "Sankey") of keywords relations (Leydesdorff and Goldstone, 2014). CorText applies the cosine similarity measurement and Louvain-algorithm for the decomposition (Leydesdorff and Goldstone, 2014). If a research topic (Shown as bars in Figure 8) in one year keeps being a research topic in the following year, the flow of the topic in the network will show as a belt linking these two bars in the map. In order to ensure the quality of visualization, we specified the number of nodes as top 123, half of the top 246 nodes.

As shown in Figure 8, associations among most topics lack of continuity and numerous topics isolate in various years. It is notable that associations among topics related to health and medicine have strong continuity in the last ten years and split or merge into different subdivisions, with topics of other subfields also associate with these subdivisions. This conforms to the fact that topics related to health has a tremendous impact on people's life so that relevant studies gain continuous attention. People are increasingly concerned about their health, search more health information and use these information for the purpose of health care. Consequently, numerous studies of information behavior research study information needs or patterns of information behavior in health or clinic context, which is verified by stable continuity of associations with "health information needs", "health information seeking" and other topics related to health context such as "health literacy", "consumer health information" and "health information". It is worth noting that in recent years, topics referring to social network such as "social media" and "Facebook" are frequently associate with topics related to health or medicine. It is because sources of health information have also evolved from authoritative sources like journals or journals to the more dynamic or user-generated contents such as social networks (Wong and Cheung, 2019). Emerging topics like "mobile health" and new devices such as "smartphone" also associate with topics of medicine. This predicts an emerging trend of research on patterns of information behavior via new channels of health information. Besides, in light of the discipline nature, topics concerning medical informatics also merge into associations among subdivisions of health context. In short, in addition to topics related to health or medicine, the associations among most topics are unstable and varies in different years.

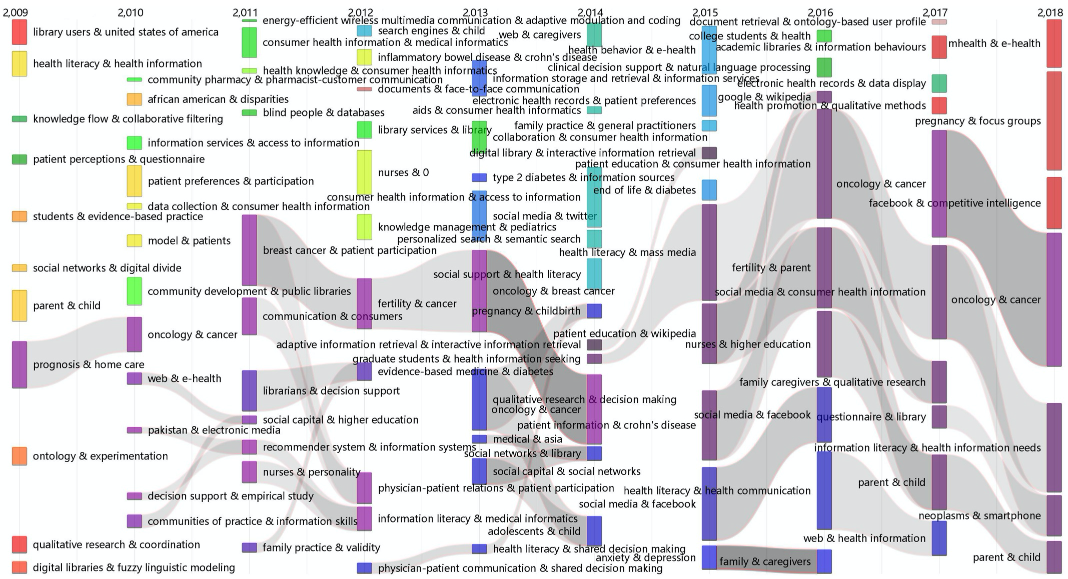

Figure 8. Evolution of associations among topics in information behavior research (2009–2018)

Analysis of the development status of six sub-communities

To describe the development status of five sub-communities in the past decade, we developed a strategy map for this research (see Figure 9), which converts the static network indictors to dynamic features in order to depict the internal relationships and external interactions among five sub-communities (Law *et al*., 1988; Hu *et al*., 2011). Strategy map is a plane rectangular coordinating system based on two measurements: centrality and density (Law *et al*., 1988). Centrality is used to measure the strength of external relationships between topics, while density is used to measure the strength of internal relationships (Liu *et al*., 2016). In a strategy map, the *y*-axis represents density (here, of the sub-community). The greater the density, the more cohesion and maturity the community shows. The x-axis represents the centrality, here indicating the strength of correlations between sub-communities. The greater the centrality, the greater the correlation between this sub-community and other sub-communities. The sub-community with a great centrality tends to be core research area in a research field. The origin of the coordinating system was calculated based on the average centrality and density of the six sub-communities.

As shown in Figure 9, C1 are located in the first quadrant with both relatively high density and centrality, demonstrating that this sub-communities not only have strong internal collaborations, but also externally interact with other sub-communities. Thus, compared to other subdivisions, research of health or medical context is the dominant subfield of information behavior research over the last ten years. With low centrality and high density, C5 and C6 are located in the second quadrant, showing that these two sub-communities have strong cohesion and maturity, but have few associations with other sub-communities. It is because that studies centered on child and youth could be seen as a part of patient-centered care, and mostly associate with those topics in C1. For the community of C6, it represents a sub-discipline of information science and has a relatively mature self-development and seldom associate with topics in other sub-communities.

In contrast, C2 is in the third quadrant of the coordinating system, with relatively low density and centrality, indicating that this community loosely associates to its internal topics and has few connections with other communities. The reason may be that as a context, C2 has complex topics in it. These topics are mostly related to emerging technologies and approaches, the continuous revolution of technologies or contexts distract researchers from various fields. Consequently, topics in this community are unstable and heterogeneous, resulting in rare associations among them and less robustness of this community.

Located in the fourth quadrant, C3 and C4 with relatively high centrality and low density both raise concern on information literacy of people in various fields. The possible explanation may be that the rapid development of information technology promotes the continuous expansion of information literacy research. Significant differences exist in the understanding of information literacy among different disciplines and industries, especially education and other industries of practice, indicating that unified theoretical framework and related concepts in this field need to be further improved.

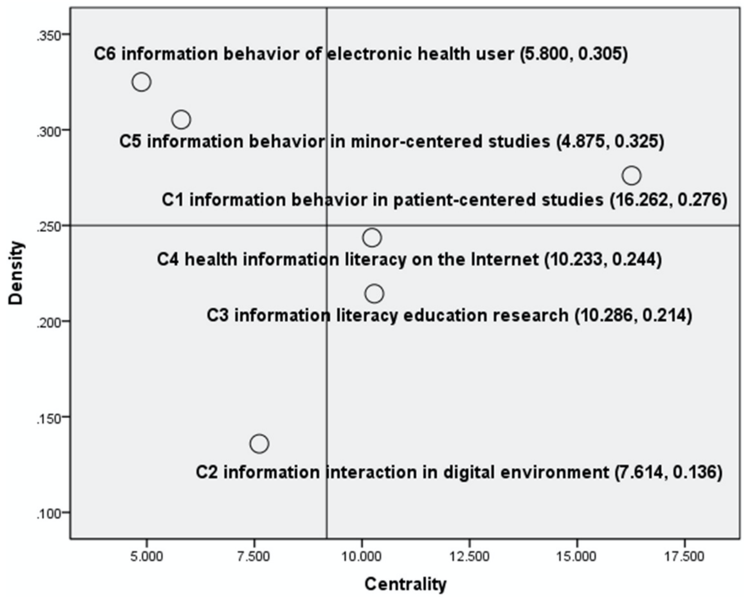

Figure 9. The strategy map of six sub-communities

Discussions and implications

In this research, we investigated topic distribution, topic communities, topic association structure and evolution, development trends of subfields in information behavior research from 2009 to 2018. Following conclusions have been drawn with the discussion with previous research.

Topic distribution and associations

According to the description of keywords and its frequency, Table 2 shows that distribution of topics in this field is unbalanced, which continues the trend of topic distribution in this field in previous studies (Vakkari, 2008; Greifeneder, 2014; Eungi, 2017). As shown in Figure 1, these dominant topics cluster into several communities including information seeking behavior in health context, context of social media, information needs in health context, information searching behavior and retrieval, and information behavior research in medical informatics. These communities construct building blocks in the structure of the field, with health-information-related context constituting the dominant. Findings help researchers understand hot spots, diversity of topics, main subfields, and how topics are extended to different contexts, such as health information or social media, which will guide their research in the field.

Though Greifeneder (2014) found that studies began to move into the focus of information behavior centered on the topic of special needs, but the types of them are limited shown in this study. As shown in Figure 2 to Figure 6, research groups are mostly patients, elderly, students or adolescents whose characteristics of the occupation and organization are obvious. In general, findings of this study show that more concern are raised on the fields of medicine and education, whether in the field of information literacy, health information behavior or other subfields. Differences in identity and occupation, as well as in work and life scenarios, lead to diverse information needs and information behavior patterns of groups. Research on diverse groups can expand the scope of this field. The investigation of information needs or patterns of marginalized groups, vulnerable groups and special groups could help them improve their information literacy, so as to better adapt to the rapidly developing information society, shorten the information gap and promote social equity.

The evolution of associations among topics in Figure 8 shows that associations among topics in health context are stable and have a strong continuity, which validates the Vakkari's (2008) prediction of trends in this subdivision. Apart from topics related to health or medicine, associations among most of these topics lack of continuity, partly due to the emerging context and technologies in these years distract researchers from various fields. This may have a negative effect on maturity or in-depth analysis of specific information behavior patterns. As Boyack and Klavans (2014) noted, the lack of research continuity of social science or humanities is a common pattern, which may result from a lack of financing or scientific infrastructure. Longitudinal studies in this field may contribute to maturity or systematicness of related work, and adequate support is also necessary for profound studies of this field.

Research on practice of health information

The network of health literacy on the Internet in Figure 5 elucidates that this subfield pays more attention on health information need and health information seeking. As a cross concept of health literacy and information literacy, health information literacy contains five aspects: awareness of health information need, accessing health information, analysis of health information, discrimination of effective health information and making decisions (Nyman *et al*., 2018). Results in Figure 5 shows that little attention have been paid on the last three aspects, and there is still room for the improvement in the maturity of this community as shown in Figure 9. Emerging information technologies and media result in massive data, accompanying with large number of false health information and health rumors, which has a negative impact on people’s health decision-making. In addition to access to health information, more concern on how users discriminate, select valuable health information and further use them for making health-related decisions could be considered in future, thereby making this subfield more mature.

As a sub-community of medical informatics shown in Figure 7, health information behavior has always been noticed and explores people's access to health information, information behavior patterns, and related knowledge about disease prevention (Brashers *et al*., 2002). Findings in strategy map show this sub-community has few associations with other communities, especially weak links to social media context as shown in Table 5, indicating a great potential for research between these two fields. Electronic health record seems to raise more concern of medical informatics in analysis of patients’ health information or treatment effectiveness (e.g., Strekalova and Yulia, 2017). However, a large volume of patient-generated health outcomes data have been created or recorder by patients or medical groups in social networks or media, which is voluntarily contributed and not limited to a single geographic location or specific groups (Ru and Yao, 2019). These patient-generated health outcomes data with rich information provide a valuable data source for health-related information behavior research. Data generated by patients or professionals in social media might promote future research on figure out users’ information needs, and how they use health information for treatment effectiveness or health-related quality of life.

Approaches and issues in digital environment

Anderson (2008) predicted that big data analytics will dominate in information behavior research in future. However, findings reveal that qualitative methodology such as focus group, interview still dominate in this field, especially in research of medical groups, which is consistent with Vakkari’s (2008) findings. The possible reason is that lots of exploratory topics of interest such as information needs of specific groups or natural contexts could not draw on automatic analysis. However, this study find that more quantitative methods and emerging approaches have been used to explore information behavior patterns in digital environments. On the basis of new approaches such as log mining, machine learning, massive data of users and behaviors provide abundant samples for predication of user characteristics or behaviors, thus optimizes system design and improves user experiences. Information behavior research focused on evaluation of information system initially (Wilson, 2000), and Fisher and Julien (2011) advocated that more attention should be paid to information behavior design. With emerging technologies and methods, more studies of information behavior could be applied to explicit connection between user and system level, which brings implications for work in the field of information systems. Likewise, problematic practices of new technologies should also raise concern on data validity or personal privacy, which challenge academics and practitioners to resolve related issues.

Albeit studies pertaining to information quality shown as a smaller branch in digital environment in Figure 3, it will develop into an important research trend in future. Problematic practices of emerging technologies and explosive growth of user generated content in social media also cause lots of problems. Misinformation on social media has become more prominent in recent years (Flynn et al. 2017; Lazer et al. 2018). The truth and fake information coexist in massive user-generated content and has negative effects on user information activities, which places higher demands on people's information literacy. Results pertaining to information literacy in Figure 4 also reflect insufficient research on how to deal with false information. From the perspective of user information behavior, apart from research on how people collect and search information, users' critical ability to effectively identify, create, disseminate information and reuse information is also important (Sullivan, 2019). Meanwhile, as a producer in information interaction, how to avoid a large amount of spam and becoming a communicator of redundant information are also worthy of attention in future research.

Except for fake information in network environment, the topic of privacy in Figure 3 also indicates another trend. Massive individual's personal information is transmitted across networked technologies such as Facebook, Twitter, etc., which is beyond individual's control. Awareness on how people handle these personal information has gradually increased in recent years (e.g., Feng and Denise, 2019). The problematic practices of social media, such as Facebook's invasion of personal privacy (Vishwanath *et al.*, 2018), raise wide concerns for personal information protection, and efforts are needed on the improvement of industry practices to protect personal information of different groups in digital age. Personal information protection or privacy-related issues in digital contexts challenge researchers or practitioners on innovation of theories and approaches. Except for psychology or behavioral patterns of personal information management, differences among various culture and marginalized groups also deserve comparison in the field.

In general, information behavior research involve various contexts (e.g., health literacy, user interface, attitudes, individuals' behavior), covering lots of disciplines including library and information science, medicine, computer science, psychology and so forth. Human interactions are increasingly supported by digital and networked technologies and extend the border of information behavior. Collaborations among researchers in different fields will facilitate in-depth analysis of more complex issues and the flow of information. In this regard, cross-disciplinary research of information behavior should be supported in order to provide a comprehensive understanding of human information behavior from both technology and humanity perspective, which contributes the innovation of theories and approaches in information behavior research.

Limitations and future research directions

We acknowledge that this study has some limitations.

Firstly, we selected only publications from the WOS database as the data sample (i.e., the literature in other databases was not covered), thus inevitably causing omissions of relevant literature and deviation from the real state of this field. In order to keep track of development in this field, future research can duplicate this effort by using different databases for the literature sample for much longer time span (such as 20 years or even longer time span). As one of the main bibliometric database in the world, Scopus has more data and types than WOS, and the countries of the data sources are more balanced, which can better reflect the international distribution of information behavior research (Chen J, 2015). Besides, some literature, such as poster, book review, and book chapter, have not been included in this article as analytical data, which can be considered in the future for many of them involve information behavior research.

Secondly, this study raise more attention on the structure and associations among topics of information behavior research, few efforts have been put into in-depth analysis of reasons behind the phenomenon. Therefore, future studies could explore factors of associations, mergence and extinction of these topics. In order to improve the visualization of details, as Vargasquesada (2010) shows in his study, future studies could present structures of the co-word network in a time-series record drawing on heliocentric maps.

Thirdly, findings in this study show that topics in information behavior research cover various fields such as computer science, medicine, education, information science, psychology, etc., indicating the trend of interdisciplinary research in this field. Co-citation, co-authorship or diversity mectrics could invesitigate the integration of knowledge from various disciplines (e.g. Porter and Rafols, 2009; Karlovcec and Mladenic, 2015; Rafols and Meyer, 2010). Thus, future research should apply methods mentioned above to explore the interdisciplinarity of information behavior research.

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