Journal of Informetrics 10 (2016) 132–150

Contents lists available at ScienceDirect

Journal of Informetrics

journal homepage: www.elsevier.com/locate/joi

Visualizing the intellectual structure of information science (2006–2015): Introducing author keyword coupling analysis

Siluo Yang[a,c,*], Ruizhen Han[a], Dietmar Wolfram[b], Yuehua Zhao[b]

[a] School of Information Management, Wuhan University, Wuhan 430072, China
[b] School of Information Studies, University of Wisconsin-Milwaukee, P.O. Box 413, Milwaukee, WI 53201, United States
[c] School of Public Management, Xiangtan University, Xiangtan 411105, China

ARTICLE INFO

Article history:
Received 2 August 2015
Received in revised form 2 December 2015
Accepted 2 December 2015
Available online 8 January 2016

Keywords:
Author keyword coupling analysis
Information science
Author bibliographic coupling analysis
Bibliometric mapping

ABSTRACT

We introduce the author keyword coupling analysis (AKCA) method to visualize the field of information science (2006–2015). We then compare the AKCA method with the author bibliographic coupling analysis (ABCA) method in terms of first- and all-author citation counts. We obtain the following findings: (1) The AKCA method is a new and feasible method for visualizing a discipline's structure, and the ABCA and AKCA methods have their respective strengths and emphases. The relation within the ABCA method is based on the same references (knowledge base), whereas that within the AKCA method is based on the same keywords (lexical linguistic). The AKCA method appears to provide a less detailed picture, and more uneven sub-areas of a discipline structure. The relationships between authors are narrow and direct and feature multiple levels in AKCA. (2) All-author coupling provides a comprehensive picture; thus, a complete view of a discipline structure may require both first- and all-author coupling analyses. (3) Information science evolved continuously during the second decade of the World Wide Web. The KDA (knowledge domain analysis) camp became remarkably prominent, while the IR camp (information retrieval) experienced a further decline in hard IR research, and became significantly smaller; Patent analysis and Open Access emerged during this period. Mapping of Science and Bibliometric evaluation also experienced substantial growth.

1. Introduction

Documents are carriers and recorders of knowledge. In today's knowledge era, the analysis and visualization of knowledge networks and intellectual structures based on documents have become increasingly important at all levels (countries, institutions, individuals, and other entities) and fields (economics, culture, technology, and other areas), along with the continuous development of science and technology. On the one hand, knowledge records are now widely available in digital form, and sufficient computing power is readily available for users to deal with large-scale knowledge networks (Zhao & Strotmann, 2008b). On the other hand, vast amounts of knowledge and information become a challenge for users in big data environments; the detailed analysis of complex and heterogeneous knowledge requires advanced tools and the continuous improvement of technology (Shiffrin & Börner, 2004).

* Corresponding author. Tel.: +86 18040599879.
E-mail address: 58605025@qq.com (S. Yang).

http://dx.doi.org/10.1016/j.joi.2015.12.003

The study of knowledge networks in general can be presented in a three-dimensional framework that includes approaches, networks types, and aggregation levels (Yan & Ding, 2012). Compared with analyses at the paper, journal, and institution levels, author-level analysis maintains a good balance in granularity and benefits the research of scholars in addition to their papers (Zhao & Strotmann, 2008b). Author co-citation analysis (ACA) is the most widely used method for the empirical analysis of disciplinary paradigms, and it has been frequently studied and improved. Bibliographic coupling was proposed as early as 1963 by Kessler (1963). The author coupling relationship has received significant attention and application in recent years; it can provide important and distinctive insights into the intellectual structure and evolution of a certain field (Zhao & Strotmann, 2014). However, coupling analysis in informetrics is often focused only on bibliographic coupling.

Bibliographic coupling is defined as two documents sharing one or more of the same items in their reference lists; this case implies that the two documents share a common research topic. A document comprises different knowledge units, which can thus be shared (overlap) by two documents. Author bibliographic coupling analysis (ABCA) extends bibliographic coupling from the document level to an author-aggregated approach (Zhao & Strotmann, 2008b). Accordingly, this sharing of knowledge units results in several types of author coupling, such as author keyword coupling, author title-word coupling, author bibliographic coupling, and author journal coupling. Because papers containing common terms may imply a common, specific research topic (Morris & Yen, 2004), similarly, we can introduce author keyword coupling analysis (AKCA), which expands the keyword co-occurrence relationship to the author level, establishes author relationships through the keyword coupling strength of authors' oeuvres, analyzes the authors of the same research themes, and then describes the knowledge structure of a field or discipline. Although all- and first-author methods can produce different results, and although some scholars have studied all-author-based and first-author-based ACA (Zhao & Strotmann, 2008c), studies that compare all- and first-author counting methods in coupling analysis are still rare. In first-author counting, only the first author of a publication is considered; in all author counting, all authors are considered equally.

In the present study conducted at the first-author and all-author levels, we introduce the AKCA method and compare it with the ABCA method using information science (IS) as the discipline of focus. Specifically, this research aims to answer the following:

(1) What are the differences between the analysis of author knowledge networks based on ABCA and AKCA and the study of the intellectual structures of research fields? Are they different in terms of the first- and all-author counting?
(2) What was the intellectual structure of the IS field during the period of 2006–2015? How did it evolve between 1996–2005 and 2006–2015?

2. Related studies

2.1. Visualization of the intellectual structure of IS

The mapping of knowledge domains is an important topic in IS. Some IS researchers often visualize their own field when mapping knowledge domains because this type of study requires expert domain knowledge (Zhao & Strotmann, 2008a). White and Griffith (1981) introduced ACA and visualized IS for the period 1972–1979. Persson (1994) analyzed the Journal of the American Society for Information Science and Technology (JASIST) based on ACA and found that the ACA map closely resembles the map of IS produced with other methods. Later, White and McCain (1998) mapped the IS field by using 12 core journals for the period of 1972–1995 and analyzed the evolution of IS over an eight-year period by showing its two sub-fields, the distribution of authors, and other aspects. Following the same method and the journals of White and McCain (1998), Zhao and Strotmann (2008a) enriched the classic ACA such that it employs both orthogonal and oblique rotations in the factor analysis; they then mapped the field of IS for the period 1996–2005. Zhao and Strotmann (2008c) also found a number of differences between all- and first-author-based ACA in IS. Klavans and Boyack (2011) mapped IS at the document level using both local and global methods to provide a case illustration of the differences between the methods. Jeong, Song, and Ding (2014) proposed a new method for measuring the similarity between co-cited authors by considering authors' citation content in IS, and they found that their proposed approach provides more details about the sub-disciplines in the domain than traditional ACA.

Another approach used to visualize a discipline structure is co-word analysis, which has several advantages (direct, objective, and others) and disadvantages (polysemy, synonyms, and others). Specifically, only some keywords (often about 100) have been used in the co-word matrix, which doesn't completely represent a field. Yang, Wu, and Cui (2012) compared three visualization methods, namely, cluster tree, strategy diagram, and social network maps. They integrated different results together into one result through the co-word analysis of medical informatics and found that the three visualization methods have unique characteristics. Milojević, Sugimoto, Yan, and Ding (2011) composed a suite of analyses of words in article titles to reveal the cognitive structure of Library and Information Science (LIS) and found that LIS consists of three main branches: libraries, information, and science. Wang, Qiu, and Yu (2012a), Wang, Li, Li, and Li (2012b) proposed a semantic-based co-word analysis, which can integrate experts' knowledge into co-word analysis effectively and can improve the veracity of co-word analysis. Ravikumar, Agrahari, and Singh (2015) explored the intellectual structure of scientometrics for the period of 2005–2010 using text mining and co-word analysis; those words were extracted from the keywords, titles, and abstracts of the articles manually.

Scholars are now gradually paying attention to direct citation analysis (Boyack & Klavans, 2010). Zhang, Janssens, and Liang (2010) showed that direct journal citation can reveal the academic influence of journals as well as the theme evolution and field division of periodicals. Wang et al. (2012a, 2012b) explored the direct citation relationship of core authors and revealed the knowledge communication and disciplinary structure in scientometrics. Yang and Wang (2015) analyzed the direct author citation among prolific, highly cited, and core authors in IS in China and around the world. Some authors have applied a combination of methods. Van Den Besselaar and Heimeriks (2006) proposed a method that uses title words as indicators of the content of a research topic and cited references as the context in which words gain their meaning; the authors applied such method to visualize IS. Chen, Ibekwe-SanJuan, and Hou (2010) introduced a multi-perspective co-citation analysis method by integrating network visualization, spectral clustering, automatic cluster labeling, and text summarization.

2.2. Coupling analysis in informetrics

Coupling analysis in informetrics focuses on bibliographic coupling instead of other coupling analyses, such as keyword coupling and journal coupling (Kessler, 1963; Yang, Qiu, & Xiong, 2010). On the basis of previous findings and theoretical considerations, Jarneving (2005, 2007) compared document co-citation analysis and bibliographic coupling for mapping of the research front and suggested that bibliographic coupling could be combined with a cluster method to develop a technique for scientific mapping that is complementary to the prevailing method for co-citation cluster analysis. Zhao and Strotmann (2008b) expanded bibliographic coupling to ABCA and analyzed the knowledge structure in IS. Continuing the ABCA of the intellectual structure of IS, Zhao and Strotmann (2014) recently tested and confirmed a previously made forecast by comparing knowledge-based and research-front findings in IS. In addition, Ma (2012) analyzed the relationship between author and document bibliographic coupling, as well as three calculation methods of author coupling strength, and used ACA and ABCA to visually analyze the subject structure of LIS in China. Huang and Chang (2014) employed both bibliographic coupling and co-citation analysis to analyze the evolution of the research fronts in the OLED field, identified the differences between them, and assessed the effectiveness of the two methods. Lu and Wolfram (2012) presented two static and dynamic author coupling methods: a word-based approach using vector space modeling and a topic-based approach based on the Latent Dirichlet Allocation for mapping author research relatedness.

2.3. Comparative study on knowledge unit networks

Comparing existing techniques of knowledge network analysis is very useful in determining their accuracy and advantages. Shibata, Kajikawa, and Takeda (2009) compared cluster solutions for detecting emerging research fronts from direct citation, bibliographic coupling, and co-citation at the document level and evaluated the performance of each network type in detecting a research front on the basis of visibility, speed, and topological relevance; the authors found that direct citation is the quickest and the best technique for detecting emerging research fronts, whereas co-citation is the worst. However, due to the short time window of their data, Boyack and Klavans (2010) compared the accuracies of the cluster solutions at the document level and argued that bibliographic coupling slightly outperforms co-citation analysis, with direct citation being the least accurate mapping approach. Yan and Ding (2012) explored the similarities among six types of scholarly networks (bibliographic coupling, direct citation, co-citation, topical, co-authorship, and co-word networks) aggregated at the institutional level and found that co-citation networks and direct citation networks have high similarity; the authors recommended the use of hybrid or heterogeneous networks to study research interaction and scholarly communications. Recently, Qiu, Dong, and Yu (2014) proposed five types of author co-occurrence networks, namely, co-authorship, author co-citation, author bibliographic coupling, words-based author coupling, and journals-based author coupling; and then mapped the networks of 98 high-impact authors from 30 journals in LIS.

The present study contributes to the array of approaches to understand the intellectual structure of fields by introducing author keyword-coupling analysis and comparing outcomes with author bibliographic coupling analysis for first- and all-author counting for the field of information science.

3. Methodology

We introduce the AKCA method, apply it to the IS field, and compare the results with those of the ABCA method, with consideration of all- and first-author coupling. Our data collection and analysis methods are the same as those employed by White and McCain (1998) and Zhao and Strotmann (2008b, 2014). Correlation analysis and quadratic assignment procedure (QAP) are performed to measure the similarities among four author coupling networks. Factor analysis, social network analysis, and content analysis are carried out to explore author relationships and intellectual structures in IS.

3.1. Data collection

We downloaded the complete records of all articles published during the period of 2006–2015 in 12 core IS journals (listed in Table 1) from the Web of Science (WoS) in April 2015. Although the data samples obtained in 2015 are incomplete, we believe that the incomplete samples will not significantly affect the research results because the time period of the data

Table 1
Journals used to define information science.

Information science	Total	Library automation	Total
Annual review of information science and technology	74	Electronic library	512
Information processing& management	730	Information technology and libraries	169
Journal of the American society for information science and technology	1470	Library resources& technical services	168
Journal of documentation	394		
Journal of information science	467		
Library& information science research	273		
Scientometrics	2005		

samples spans 10 years. These journals were used to define and map the IS research field by White and McCain (1998), Zhao and Strotmann (2008a, 2008b, 2008c, 2014). Although the classic data sets of the 12 journals have some deficiencies, such as the scope and criteria of the selected journals (Yang & Wang, 2015), we chose the same sets and considered the renamed journals to facilitate the comparative analysis of the evolution of IS. However, two journals ("Proceedings of the American Society for Information Science and Technology" and "Program -Automated library and information systems") were not included because we did not find any results when searching for them in WoS for 2006–2015. We found the indexing for the ASIST Proceedings ended in 2003, so it didn't overlap with the study period. For "Program -Automated library and information systems", the journal was renamed as "Program -Electronic library and information systems" since 1996. We did not include the result of "Program -Electronic library and information systems" in our study for two reasons. First, Zhao and Strotmann (2008; 2004) introduced the ABCA and revealed the intellectual structure of the IS field for 1996–2005; they used the "Program -Automated library and information systems" In order to keep the data sets consistent and the results comparable, we used the same names. Second, there were 228 articles listed for "Program -Electronic library and information systems" for the period 2006–2015, which represents about 3.6% of the total data set. When we added the 228 articles to the data set, it had little influence on the 120 authors and the results. The data set we used for the study includes 6262 records of source papers, which collectively have 244,686 references – that is, about 39 references for every source paper on average. The data set also has 17,789 author keywords (DE) and 21,949 keywords plus (ID). A total of 6247 articles have references (CR), 2487 articles have no DE, and 5030 articles have ID or DE.

Following the method of Zhao and Strotmann (2008a, 2008b), we define the weighted keywords/bibliographic coupling frequency between two authors as the number of references or keywords that these two authors' oeuvres share, although we do not normalize the frequency of each keywords (e.g., TF-IDF). Specifically, a word or reference that is used by X documents in Author A's oeuvre and by Y documents in Author B's oeuvre would contribute min(X, Y) to the coupling frequency of Authors A and B. Accordingly, an author's average coupling frequency is the sum of this author's coupling frequency and those of all the other authors in the data set that is then divided by the total number of authors in the data set minus 1 (Zhao & Strotmann, 2014). We selected these authors considering both the number of published papers and their average coupling frequencies. Two types of author coupling analyses were used in our research. First, the classic ABCA only considers first authors in the definition of author bibliographic coupling. We followed the classic ABCA method and selected the 155 most prolific first-authors with at least five published works. Second, we calculated all-author coupling. So, if a paper included more than one author, then an equal treatment was given to all authors. We selected the 188 most prolific authors with at least eight published works. The 155 (first-authors counting) and 188 (all-authors counting) authors published, respectively, 1354 (22%) and 1941 (31%) articles.

A preprocessing step was necessary to improve the quality of analysis units and to obtain satisfactory results in the science mapping analysis (Dehdarirad, Villarroya, & Barrios, 2014). In our preliminary experiment, no preprocessing step was performed; hence, the result was extremely poor, especially the clustering result and the effect of the factor analysis. In our formal study, we mainly detected duplicate and misspelled elements in the data sets of authors, keywords, and references and removed different variants of words. In the AKCA method, we proposed the content analysis technique based on the assumption that when two authors have numerous words in common, the research areas of the two authors are highly similar. First, author-provided keywords (DE) were extracted from papers, with keywords plus (ID) being those used in instances in which no author-provided keywords were available. We only used the ID entries for the small number of cases where there was no DE. We focused on the author relationship by the word co-occurrence rather than direct co-word analysis. ID is also a kind of term and can form author relationships, although they come from the titles of all references. So, the mixing of the two has only a small influence on our research results. After extracting the data, we split the phrase in the keywords into a single word and processed the uppercase and lowercase words. Thereafter, we built the "author–word" two-model matrix on the basis of the number of the same words between authors. Afterward, these words denoting the same concepts (different spellings; plural and singular forms; verbs, adjectives and nouns of the same stems) were merged manually into the most frequent word occurring in the data set, such as the words "behavior," "behavior," "behavioral," "behavior," and "behavioral." We also deleted function words, such as "the," "and," "of," and "on," because these words provide limited cognitive content. However, we did not consider synonyms, ambiguous words, or general words. We believe these situations have less influence on the AKCA results than co-word analysis, because we mainly studied the authors' relationships on the basis of word co-occurrences rather than direct co-word analysis. Moreover, manually merging these words doesn't seem to be very plausible and is difficult to conduct thoroughly. For example, there is no ideal method that can be used to deal with words that are not sufficiently specific or that carry different meanings in different textual contexts, although these may reveal a less specific and more general structure using AKCA. In the first-author AKCA method, 1741 words used 6631 times were merged into 1249 words. In the all-author AKCA method, co-authors were treated equally, and 2424 words used 15,406 times were merged into 1686 words. Accordingly, in the ABCA method, symbols such as "(", ")", "." and "." were removed, and all characters in these references were converted into lowercase letters for all the data. Although the format of these references in the WoS is not absolutely uniform, no special treatment was applied because such treatment entails a heavy workload and has minimal influence on the research results. Also, we checked a subset of the records and believe the quality of the data in WoS is relatively uniform for the most recent 10 years. In the first-author and all-author ABCA method, 31,079 and 44,483 references were used, respectively, 51,477 and 75,458 times.

We then constructed 155×155 and 188×188 author $\times$ author matrices with self-coded VBA programming. Author name disambiguation is obviously important in our study. We then manually examined and checked author names in the matrices by their full name, surname, and affiliation. Unfortunately, this removes a number of scholars of East Asian ancestry from consideration. We find the ambiguity of authors' names with East Asian ancestry is common, as many Asians share a few family names, especially, when we only consider the first letter of the first name and the last name. The authors sharing the same name were deleted accordingly; examples included "WangJ, ZhangL, KimH, KimS, ZhangP, ZhangY, YoonJ, LimS, YangC, ZhangJ" and "WangJ, ZhangX, ZhangL, KimH, KimJ, KimK, LiuY, KimS, LeeH, LeeJY, LeeS, LiJ, SunY, SongM, LiYL, LinHF, LiuXZ, LeeJH, ZhangJ, YoonJ, ZhangY" from the first-author coupling and all-author coupling, respectively. We believe that removing these Asian names did not have a large effect on the map. First, by checking the titles and keywords of these articles of deleted authors, we found these authors were mostly neither in IR nor focused in KDA, in general. But we do not know whether these authors belong exactly to some subfield of IR or KDA, which requires a more advanced method of author name disambiguation (such as ORCID). Second, if we were to disambiguate these authors, the number of the articles (that authors published) would be significantly reduced; many of these authors would be excluded from the authors set. No strict rules have been established regarding the thresholds for author selection in author coupling analysis. Thereafter, the top 120 of these authors were selected according to the ranking of their average coupling frequencies because 120 authors were used in the previous studies of White and McCain (1998) and Zhao and Strotmann (2008b) to represent the IS field. Both all- and first-author ABCA and AKCA have the same 188 (155) most prolific authors. However, they do not have the same 120 authors because we selected 120 authors according to keyword and bibliographic coupling frequencies. The keyword and bibliographic coupling frequencies were different for every author.

3.2. Factor analysis

We explored the underlying structure of authors' interrelationships to reveal the intellectual structure of IS by considering four symmetrical matrices, namely, first- and all-author AKCA and first- and all-author ABCA, in the factor analysis. White and McCain (1998) and Zhao and Strotmann (2008b) proposed this method and used loadings as a similarity measure between author and factor nodes; the result has unique advantages over traditional cluster techniques (Yang & Wang, 2015). The normalized measure, Pearson's r, was used when the factor analysis was conducted on the author matrices using SPSS 22, although the use of Pearson's r for co-occurrence metrics has been criticized and is, therefore, somewhat controversial. For example, Ahlgren, Jarneving, and Rousseau (2003) and Leydesdorff (2008) argued that instead of Pearson's r, a different similarity measure should be used, such as the cosine and Jaccard measure. However, White (2003) insisted Pearson's r performed well enough for the purposes of author co-occurrence analysis. We followed the traditional method, since researchers have no consensus on which similarity measure is most appropriate for co-occurrence normalization (Eck & Waltman, 2009). The diagonal values in the matrix were treated as missing data and replaced with the mean in that routine; the number of factors extracted was determined on the basis of Kaiser's rule of eigenvalues greater than 1 (Zhao & Strotmann, 2008b). The factors were extracted by principal component analysis and orthogonal rotation (SPSS Varimax). Zhao and Strotmann (2008a) argued that "both orthogonal and oblique in factor analysis have their own respective strengths" and "orthogonal rotation elicits a picture of authors' memberships in their general areas of expertise" (p. 930). However, the results of our test on the oblique rotations in our data set clearly indicated that orthogonal rotation was better than oblique rotation. When oblique rotations were used, incomprehensible connections emerged between factors. Moreover, orthogonal rotations in classic studies produced clear and revealing results for the IS field (White & McCain, 1998).

3.3. Visualization of factor structures

In early research, scholars usually selected tables or multidimensional scaling maps to visualize factor structures. These tools facilitate visualization and show a certain amount of information, but some novel ways of visualizing factor analysis results are more visually informative and true to the factorization it represents (Yang & Wang, 2015; Zhao & Strotmann, 2008b). In the present work, we performed a visual analysis and developed a cluster density map by using Netdraw, which features powerful network analysis functionality and ease of use. We used the map layout algorithm to place nodes on the basis of "node repulsion" and "equal edge length bias" in Netdraw. Isolated nodes were deleted. Factors were labeled upon examination of the articles written by authors who load primarily in each factor (Zhao & Strotmann, 2014). In other words, we tentatively named each factor based on manual work and summarized the common theme of those principal loading authors by the titles and keywords of published papers. In particular for the AKCA method, the "author–word" two-model

Table 2
Social network analysis of ABCA and AKCA networks.

Indicator			Network			
			First-author ABCA	First-author AKCA	All-author ABCA	All-author AKCA
Whole network analysis	Average density (Std Dev)		4.2 (8.3)	4.4(4)	17.4(40.2)	13(10.5)
	Clustering Coefficients		6.356	4.648	19.758	12.998
	Average distance		1.391	1.081	1.132	1.005
Network structural analysis	Components number		1	1	1	1
	Components node		120	120	120	120
Network node analysis	NrmDegree centrality	Maximum	20.361	26.723	8.364	15.546
		Mean	3.412	10.961	1.973	6.416
		Centralization	17.24%	16.03%	6.50%	9.29%
	nBetweenness centrality	Maximum	1.428	0.101	0.272	0.004
		Mean	0.332	0.068	0.112	0.004
		Centralization	1.11%	0.03%	0.16%	0.00%
	nCloseness centrality	Maximum	96.748	100.000	100.000	100.000
		Mean	73.104	93.025	89.466	99.539
		Centralization	47.89%	14.13%	21.34%	0.93%

matrix is mapped directly, and these factors can be easily identified and named. A factor was labeled as "undefined" if all the loadings in this factor were lower than 0.3.

We visualized the results of the factor analysis as a two-mode network of authors and factors (specialties) according to the rotated component matrix (the rotation method is Varimax with Kaiser normalization) of the factor analysis. In the loading of the authors on these factors, low loadings (i.e., those lower than 0.3) were removed because a loading represents an author's contribution and influence to a factor (specialty), and sufficiently high loadings showed that authors were important for the factor (Zhao & Strotmann, 2014). These maps show and visualize the IS intellectual structure according to the node shape, node size and color, map layout and node positions, and size and color of connecting lines. In these maps, authors and factors are represented by circular nodes and square nodes, respectively.

The color of a factor node corresponds to the number of authors whose loadings on this factor is at least 0.3; the color of each author node indicates the number of loadings higher than 0.3 (degree centrality). The size of a factor node corresponds to the sum of the loadings on this factor of all authors who load sufficiently on it (≥0.3). The size of an author node is the sum of the loadings higher than 0.3 of this author. The width and color of a line that connects a particular author to a specific factor is proportional to the loading of this author on this factor. A factor node with red (≥0.5) and thick lines connected to it represents a clear and distinct specialty. Authors' loadings higher than 0.3 on more than one factor, which are presented as more than one line that connects the author, indicate the contributions of the authors are to more than one specialty (topic).

4. Results

We first compare the four author coupling networks through social network analysis (SNA) and then examine the intellectual structure of the IS field during the period of 2006–2015 by employing first- and all-author coupling analysis. We subsequently discuss the changes in this IS structure during the periods of 1996–2005 and 2006–2015.

4.1. Comparison of the four networks

We compared the four author relation networks using SNA in order to reveal the features of these networks by fully comparing ABCA and AKCA outcomes. The outcomes also provided some mutual evidence for the results of the author maps. As shown in Table 2, the four author relation networks are compared through SNA. (1) The Component in SNA is every part of the networks. Relational networks can be divided into several parts. Relations (lines) exist between the members (nodes) of each part, whereas no relation exists between parts. We can find only one component of each author network. In other words, no isolated node (author) is found in these networks. (2) Density measures the proportion of ties in a network relative to the total number of ties possible. Clustering coefficients measure the likelihood that two associates of a node are associates themselves, and a high clustering coefficient indicates high levels of "cliquishness." Distance is the number of edges (lines) in the shortest path between each pair of nodes (John & Peter, 2011). Compared with the ABCA method, the AKCA method shows higher average density and lower clustering coefficients and average distance (Table 2). For example, the overall graph clustering coefficients are 6.356 and 19.758 in the first- and all-author ABCA, respectively, whereas they are 4.648 and 12.998 in the first- and all-author AKCA, respectively. In general, more relations (lines) are found in the AKCA method, whereas the distribution of relations (lines) is more uneven in the ABCA method. (3) Centrality refers to the "importance" or "influence" of a particular node (or group) within a network. Degree centrality is the number of ties (lines) of a node, and NrmDegree centrality is the relative and standard degree centrality. Betweenness centrality is the number of shortest paths from all vertices to all others that pass through a node, and nBetweenness is the normalized betweenness centrality. Closeness centrality is the sum of the distances of a node from all other nodes (the length of their shortest paths). Network

Table 3
Factor models and their model fits.

Input matrix	Factor number	Total variance explained	|nonredundant residuals| > 0.05(%)	Communalities		
				Range	<0.6(%)	<0.8(%)
First-author ABCA	16	81.483	214(2%)	0.376–0.94	3(2.5)	39(32.5)
All-author ABCA	22	76.272	206(2%)	0.288–0.97	25(20.83)	53(44.17)
First-author AKCA	13	83.128	77(1%)	0.689–0.929	0(0)	27(22.5)
All-author AKCA	10	81.43	74(1%)	0.541–0.93	2(1.667)	40(33.33)

node analysis shows a consistent phenomenon, and the results are shown in Table 2. These indexes (Components number, Components node, nCloseness centrality) illustrate that all nodes in the four networks have a close relation to each other on the whole. Compared with the ABCA method, the AKCA method shows higher NrmDegree and nCloseness centralities and lower nBetweenness centrality (Table 2). The mean nBetweenness centrality is extremely low (0.004), whereas the mean nCloseness centrality is extremely high (99.539). These results show that, in general, nodes in AKCA have a closer relationship than nodes in ABCA.

The QAP is a unique method of measuring relationships in relational data. It compares the value of various corresponding elements in two (or more) squares and gives the Pearson correlation coefficient between two matrices by comparing the corresponding grid values in each square. A non-parametric test is performed on the coefficients on the basis of the replacement of the matrix data (Borgatti, Everett, & Freeman, 2002). We analyze two pairs of author matrices. Exactly 155 authors and 188 authors are found in the first- and all-author coupling matrices, respectively. We did not use these matrices of 120 authors because QAP compares the corresponding grid values in each square in two matrices and would need the same number of authors as well as the exact same authors. As a result, the matrices of 120 authors do not have the exact same authors for both first-author and all-author counting. The correlation coefficients of the QAP (ObsValue) are 0.413 and 0.53 between the first-author AKCA and ABCA matrices and between the all-author AKCA and ABCA matrices, respectively. Although positive correlations are observed between the AKCA and ABCA matrices, especially in the all-author, these correlations are not very high. In addition, correlation analysis was performed on author rankings on the basis of the descending order of the average coupling frequency. The Spearman correlation coefficients of the author rankings are 0.453 and 0.53 for the first-author AKCA and ABCA and the all-author AKCA and ABCA, respectively. The abovementioned result indicates that the AKCA and ABCA matrices present a weak positive correlation; which show that AKCA and ABCA have some similarities, but are not exactly the same.

4.2. Factor analysis results

As shown in Table 3, all the four factor models in the present work have good model fits. For example, in the case of the matrix of the first-author ABCA, the resulting 16-factor model explains 81.482% of the total variance. The residuals are computed between the observed and reproduced correlations. Only 214 (2.0%) non-redundant residuals have absolute values greater than 0.05. About 97.5% of the communalities are above 0.6, whereas 67.5% of the communalities are above 0.8. The highest communality is 0.94.

The factor models from the AKCA matrices have significantly better model fits than those from the ABCA matrices. Hence, factorization is clearer in the AKCA matrices than in the ABCA matrices. For example, the 10-factor model extracted from the all-author AKCA matrix can explain 81.43% of the total variance, whereas the 22-factor model extracted from the all-author ABCA matrix can only explain 76.272%. In the all-author AKCA matrix, the minimum communality is 0.541, and only two communalities are less than 0.6. In the all-author ABCA matrix, the minimum communality is 0.288, and 25 communalities are less than 0.6. This result may be explained as follows. Keyword coupling is concentrated, whereas bibliographic coupling is dispersed. Keywords directly express and label the themes, and authors containing common keywords often share a common and specific research topic, whereas references are often used as the knowledge base of papers. References may appear in various section of a paper, including the introduction, the method, the result and the conclusion part. References often play different role (e.g. background, acknowledgements, argument), and indirectly related to the content or topic of a paper and an author. Our model fitting effect in the ABCA method is similar to that obtained by Zhao and Strotmann (2008b), Zhao and Strotmann (2014), although the data sets used cover different periods.

4.3. Intellectual structure of IS based on first authors

Following the previous research of Zhao and Strotmann (2014), we interpret major factors as specialties (loading primarily on this factor involves more than 10 authors) and minor factors as topics. A factor is labeled as undefined if all the loadings on this factor are lower than 0.3. In Tables 4–7, the size of a factor is the number of authors who load primarily on this factor; the size in parentheses is the number of authors with loadings higher than 0.3. The highest loading on a factor indicates the distinctiveness of this factor. Labeling a factor that appears to include all diverse topics of all loading authors is difficult. We combine and refine these labels and select only the most prominent theme.

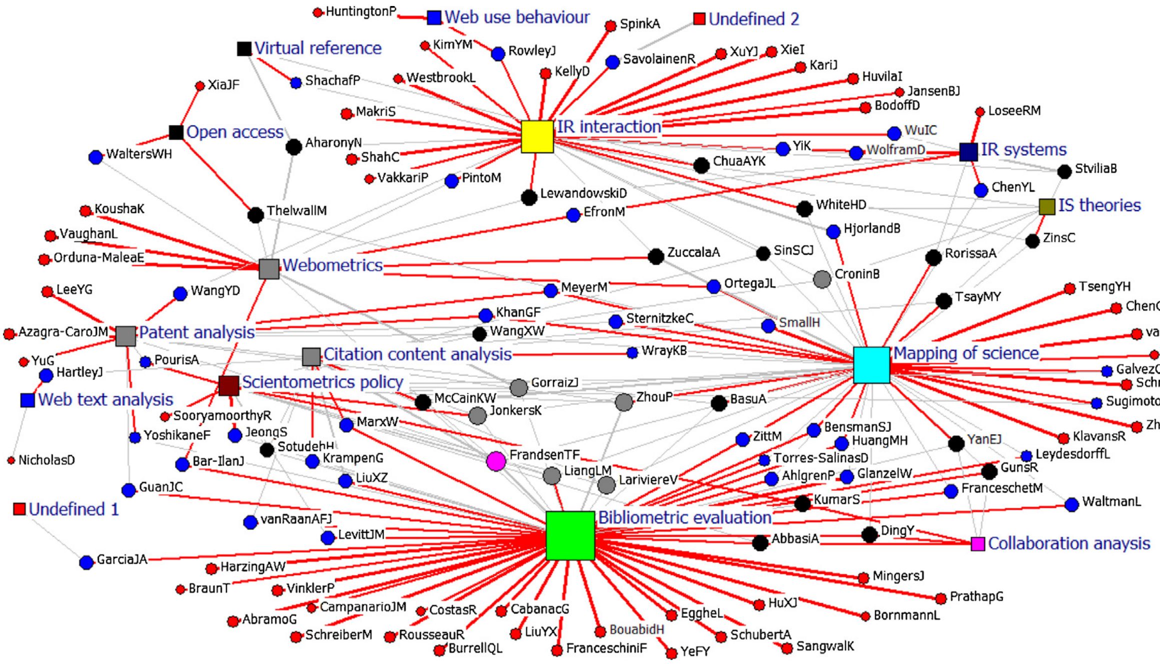

Fig. 1. Structure of the IS field in 2006–2015 as seen from the first-author ABCA.

Figs. 1 and 2 visualize the 16-factor and 13-factor models, respectively, based on the first-author ABCA and AKCA. Tables 4 and 5 show the corresponding summary of these factors' labels, sizes, and distinctiveness. Some studies found IS to consist of two largely separated camps: the information retrieval (IR) camp and the knowledge domain analysis (KDA) camp (Zhao & Strotmann, 2008b). The two-camp structure is displayed clearly in Figs. 1 and 2: the top part shows the IR camp while the bottom part shows the KDA camp. The structure of IS during the period of 2006–2015 (Fig. 1) is largely consistent with the structure shown in Fig. 2; that is, most of the specialties and topics in Figs. 1 and 2 carry the same labels.

Using the information in Figs. 1 and 2 and Tables 4 and 5, we identify a number of differences between the first-author ABCA and AKCA. First, at the macro level, the ABCA method visualizes more factors than the AKCA method (16 versus 13

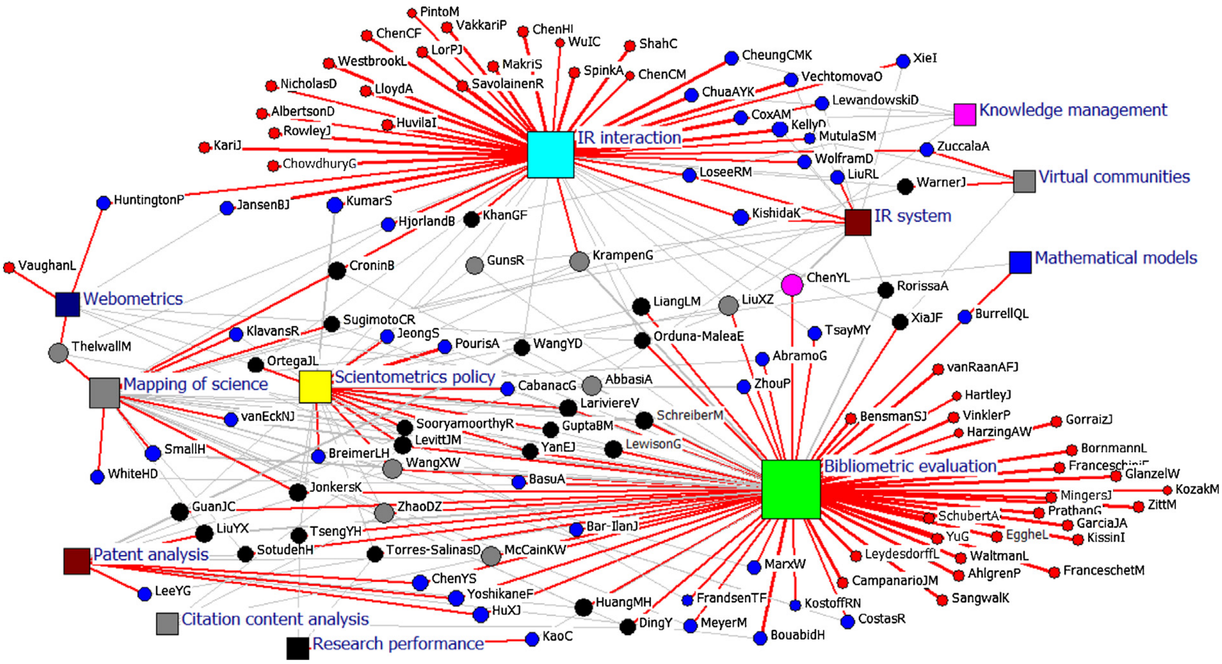

Fig. 2. Structure of the IS field in 2006–2015 as seen from the first-author AKCA.

Table 4
16-factor results from first-author ABCA of IS in 2006–2015.

Label	Size	Highest loading	Label	Size	Highest loading
bibliometric evaluation	38(54)	0.945	open access	3(3)	0.677
mapping of science	22(46)	0.892	IS theories	1(7)	0.555
IR interaction	20(31)	0.89	collaboration analysis	1(5)	0.564
webometrics	6(14)	0.937	web text analysis	2(2)	0.696
patent analysis	6(14)	0.902	web use behavior	2(2)	0.792
scientometrics policy	6(17)	0.79	virtual reference	2(3)	0.527
citation content analysis	5(14)	0.745	Undefined 1	0(3)	0.302
IR systems	6(9)	0.786	Undefined 2	0(3)	0.487

in Tables 4 and 5, respectively). The specialties in Fig. 1 and Table 4 are more evenly distributed in size, unlike those in Fig. 2 and Table 5, which show very large and very small factors. In Fig. 2, most of the researchers focused on bibliometric evaluation and IR interaction (55 and 36 in terms of size in Table 5, respectively). Most of the authors with only one loading of more than 0.3 belong to the two specialties (corresponding to the red author nodes). Others small topics overlap with bibliometric evaluation and IR interaction, as shown by the non-red author nodes in the other topics in Fig. 2. In general, the specialties in Fig. 1 appear to overlap less than those in Fig. 2; the authors in Fig. 1 have fewer secondary loadings than their counterparts in Fig. 2. These results are consistent with the social network analysis in Table 2. The relation within the ABCA method is based on the same reference, and the granularity of reference is fixed at the paper level. The relation within the AKCA method is based on the same keywords, which have flexible forms and diverse contents. Thus the AKCA method has more levels and aspects to reveal intellectual structures than the ABCA method, which results in the uneven distribution of factor sizes.

Second, the specialties and topics according to Figs. 1 and 2 have different sizes, scopes, and emphases at the micro level; a few small research topics do not appear in Figs. 1 and 2. Some topics only appear in Fig. 1 on the basis of the ABCA method (including open access, IS theories, collaboration analysis, web text analysis, web use behavior, and virtual reference), whereas others only appear in Fig. 2 on the basis of the AKCA method (including virtual communities, knowledge management, research performance, and mathematical models). In Fig. 1, the KDA camp is dominated by research on bibliometric evaluation and science mapping, followed by research on Webometrics, patent analysis, scientometrics policy, citation content analysis, and a small research topic on collaboration analysis. In the IR camp, most of the researchers focus on IR interaction. Moreover, some researchers are spread across several small themes: IR systems, open access, IS theories, web text analysis, web use behavior, and virtual reference. In comparing Figs. 1 and 2, we find that the KDA and IR camps are concentrated in the research on bibliometric evaluation and IR interaction, respectively. Substantial differences in size between Figs. 1 and 2 can be observed in the mapping of science specialty; it is significantly stronger in Fig. 1 than in Fig. 2 (22 versus 7 of the sizes in Tables 4 and 5, respectively). We find that researchers reference many of the same papers in the field of science mapping, especially in some classic documents, while using different keywords (especially some bibliometric terms) because knowledge mapping is widely used in various fields and is visualized by using bibliometric theory and methods.

Third, the KDA and IR camps in Fig. 2 based on the AKCA method have fewer contacts and connections than the two camps in Fig. 1 based on ABCA. One of reason is two camps share some common knowledge base (reference) while use different keyword to description and presentation papers. In Fig. 1, the IR systems specialty has many connections with the KDA camp; IS theories and IR systems connect the two camps. The IR camp (virtual reference, IR interaction, and IR systems) has many connections with the KDA camp (Webometrics and mapping of science). In Fig. 2, the two loosely connected camps are connected by Webometrics, scientometrics policy, IR systems, and other topics. Specifically, two major specialties (bibliometric evaluation and IR interaction) integrate the entire IS field. Among the authors who have multiple memberships (Figs. 1 and 2), almost all belong to the KDA camp or connect the two camps. For example, Aharony N, Lewandowski D, Pinto M, and Rorissa A in Fig. 1 and Huntington P, Ortega JL, Xia JF, and Cronin B in Fig. 2 connect and belong to the two camps. In Figs. 1 and 2, the two camps are connected largely through web-related topics. For example, Chen CM is famous in science mapping but belongs to the IR interaction specialty in Fig. 2. By examining the data sample, we find that Chen CM published nine first-author papers, the contents of which are mainly related to mapping and visualization and partly related to digital

Table 5
13-factor results from first-author AKCA of IS in 2006–2015.

Label	Size	Highest loading	Label	Size	Highest loading
bibliometric evaluation	55(78)	0.925	virtual communities	1(4)	0.618
IR interaction	36(51)	0.91	knowledge management	0(5)	0.377
scientometrics policy	9(30)	0.782	research performance	1(3)	0.661
mapping of science	7(29)	0.737	citation content analysis	0(4)	0.45
patent analysis	6(14)	0.689	mathematical models	0(2)	0.531
IR system	3(13)	0.702	Undefined	0(1)	0.315
Webometrics	2(8)	0.766			

libraries and information filtering. However, four papers of Chen CM on mapping that were published in JASIST do not have DE and ID entries in their WoS records.

Fourth, we find that 100 authors are included both in first-author ABCA and AKCA maps (Figs. 1 and 2); 40 authors appear only in Figs. 1 and 2 because of the difference of keyword and bibliographic coupling frequencies. 59 of 100 authors have the same field (topic); for example, Egghe L, Ding Y and Glanzel W belong to Bibliometric evaluation both in Figs. 1 and 2. However, some authors belong to different field. For example, Lariviere V belong to same camp (KDA) but different field (Mapping of science and Bibliometric evaluation in Figs. 1 and 2), while Hjorland B belong to different camp and different field (Mapping of science and IR interaction). There are mainly two reasons accounting for this. Firstly, Author's research involves more than one areas; for example, Hjorland B have principal loadings (0.629) on Mapping of science and second highest loadings (0.489) on IR interaction in Fig. 1, while Hjorland B have principal loadings (0.673) on IR interaction and second highest loadings (0.452) on Mapping of science in Fig. 2. Secondly, the relationships within the ABCA and AKCA methods are based, respectively, on the same references and keywords. For example, Lariviere V have principal loadings on Mapping of science because these authors in the factor have many of the same references and share the topic of science mapping in Fig. 1; while Lariviere V have principal loadings on Bibliometric evaluation because they have many of the same words and share the topic of bibliometrics evaluation in Fig. 2.

References and keywords are community markers of authors' scholarly behavior and reflect the sociability of invisible colleges. Reference or citation analysis is widely used on the basis of a fundamental assumption, that is, referencing is a strict scholarly behavior in which a cited paper (author) and the citing paper (author) share relevant or similar themes to a certain extent. A keyword is extracted from a given paper by an expert. Different researchers use the same keywords to express and label the common theme or concept because they can accurately grasp the same content, concept and jargon in a discipline or field. Keywords are directly concentrated and refined from a paper. If the papers of two authors have the same keyword(s), the papers and research topics of the two authors have similarities; these representative relations of authors represent the activity of academic community. Thus, the ABCA and AKCA methods demonstrate the knowledge structure of a discipline. Authors related by keywords and references have similarities. Moreover, the results of the ABCA and AKCA methods are consistent to some degree.

However, the ABCA and AKCA methods have different basic principles. Although both of them are author-aggregated approaches, the differences in their principles lead to a few differences in their analysis of the intellectual structure of the same discipline or field. The relationship within the ABCA method is based on the same references (knowledge base). The relationship strength between two authors can be defined as the number of references shared by the oeuvres of the two authors. The relationship within the AKCA method is based on the same keywords. The relationship strength under this method is based on the number of the same keywords used by two authors. The relatedness between authors is measured differently. The AKCA method uses author keyword frequency rather than reference counts as a measure of the relatedness between authors and as a tool to map discipline structure (Zhao & Strotmann, 2008b). Authors reference papers of different fields and topics, and articles are based on a broad knowledge base. Thus, more themes can be found with the ABCA method. However, authors often use the same keywords to express the topic of papers (in particular, the use of a number of general vocabularies), so the relationship between authors becomes closer. This condition is consistent with the distributions of the numbers and frequency of references and keyword, which can also be seen from the mean value of NrmDegree centrality, nBetweenness centrality, nCloseness centrality in Table 2. Thus, fewer themes can be found with the AKCA method; the factors overlap and are unevenly distributed in size. But this is just speculation; this will need to proven in future research, by using topic analysis, for example, to address similar vocabulary to explore these effects.

AKCA more directly reveals intellectual structure than ABCA because a word represents an idea, topic, or concept to which it is related with special authors. Establishing the relationship between two authors by reference involves certain limitations. First, citing theory often explains the reason why an author cites a paper. However, some existing citing theories do not indicate the content relevance or similarity between citing papers and cited papers. For example, the normative theory of citing suggests that "citations are a way to acknowledge intellectual debts," whereas the social constructivist theory of citations indicates that persuasion is a major motivator to cite a source; the purpose of science papers is that an author convinces others by mere persuasion (Nicolaisen, 2007). Second, the reason for citing literature is varied. Two papers may completely have different reasons or aspects to reference an earlier document. An article may refer to its method, whereas another may refer to the results. Thus, the content of two documents is unlikely to be similar. Third, some citations are found in the foreword, introduction, body, discussion or conclusion sections. The citing content and extent, therefore, are not the same. Finally, specific types of influential articles are cited while others are not. The Matthew Effect related to citations also covers and affects the authenticity of the ABCA method (MacRoberts & MacRoberts, 2010). These factors result in the factor models from the ABCA matrices having worse model fits than those from the AKCA matrices.

However, author coupling analysis using keywords also has some disadvantages. Many journals (including JASIST) require authors to select descriptors from a pre-defined ontology, and these are used as the keywords. Very often they don't fit the paper very well. Often they are chosen from an IR (or search) point of view rather than a content point of view. For example, JASIST has no descriptor that is an adequate proxy for 'science mapping' or 'knowledge domain visualization'. In other cases journal staff members choose the keywords. Thus, keywords are a mixed bag, and have the features of richness and versatility. Some keywords are very general, and others are very specific. This leads to some problems, including the over-aggregation of some structures. Also, keyword distributions are more concentrated than references; word-relation matrices are less sparse and likely to be noisier than citation relations (Zitt, 2015). There are typically far fewer keywords than references, leading to

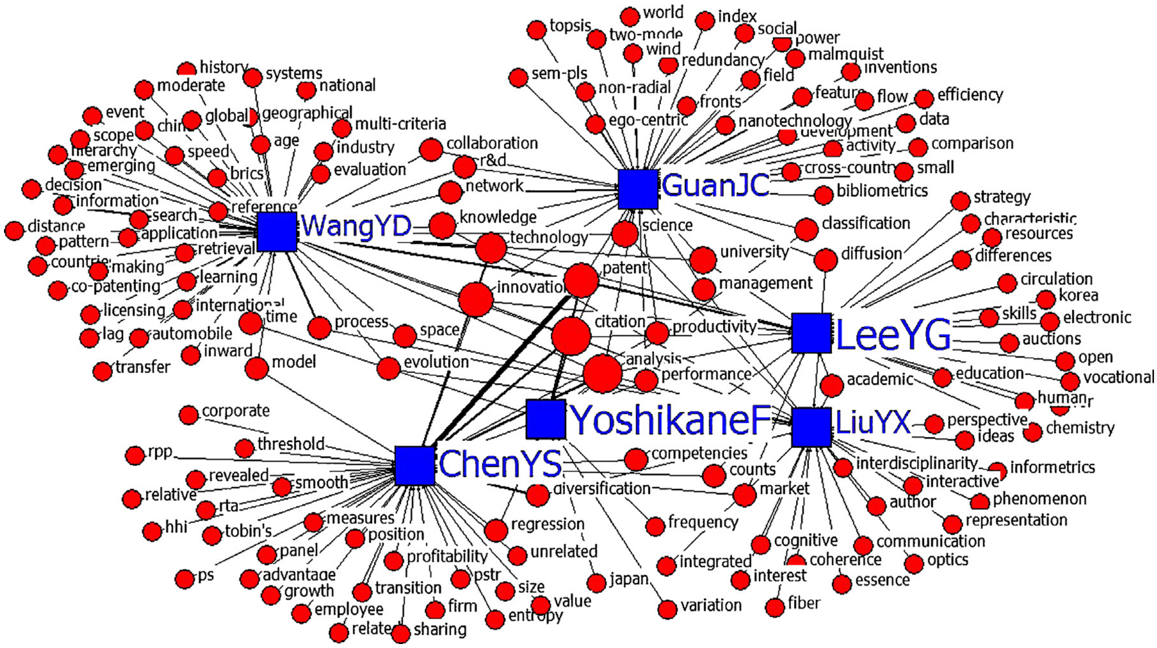

Fig. 3. Structure of "patent analysis" factor in the IS field in 2006–2015 as seen from the first-author AKCA.

a lack of specificity, a lack of sparseness in the matrix, and a lower overall signal from keywords than from references. Our finding that AKCA is less specific than ABCA stems directly from these properties of keywords. In addition, the AKCA method has more levels and aspects to reveal intellectual structures than the ABCA method, which result in the uneven distribution of factor sizes. First, keywords have different ranges and scopes, including macro, meso, and micro levels. For example, some general terms (bibliometrics, information, management, etc.) and many relatively specialized words (synchronous, pagerank, and obsolescence, etc.) are included. Second, words have various grammatical categories, such as verbs, nouns, and adjectives. The noun and verb forms of keywords can reflect a paper's core contents, whereas the adjective form reflects the attributes and characteristics of one aspect of a paper. Thus, the diverse, pluralistic, and multi-level relation between authors can be built on the basis of keywords. In particular, some general terms often have high frequency and are widely used by authors. These factors result in a more general and uneven structure of maps in AKCA. This method needs also to facilitate the precise understanding and correspondence of word semantic aspects to overcome polysemy and synonyms. These issues depend largely on the automatic understanding of text context and content in computers. But, we think keywords reflect and label papers' content in general, although there may be many exceptional cases, even if they are chosen from an IR (or search) point of view (topic retrieval). We found also that authors are asked to provide keywords in their own words in most of the 12 journals (except JASIST). Furthermore, we focused on the author relationship by word co-occurrence rather than directly co-word analysis, so the special cases have small influence on our research result. Besides, it is well known that co-word analysis is one of the main approaches used to discover and visualize a disciplinary structure; many co-word analyses only used keywords as well.

Moreover, AKCA has an advantage for labeling and naming these factors (specialties). Given that authors, especially some prolific authors, often write about a range of topics, we consider factor labeling to be easier with the AKCA method than with the ABCA method, for which labeling is based on authors who share references. Considering the meaning of AKCA, i.e., authors sharing keywords, we believe that labeling factors is direct and easy when common words of the loading authors are used. We can map directly the "author–word" two-model matrix and easily find and name these factors. The "patent analysis" factor in the IS field in 2006–2015 is used as an example (Fig. 3). The size of the labels of an author node corresponds to the loadings on this factor by the authors. The width of a line that connects a particular word to a specific author is proportional to the frequency of this word on this author. The size of a word node corresponds to the degree centrality of a word on this "author–word" network. We can label the factor using the common words (sharing among authors) at the center of Fig. 3 and adjunctively determine such factors according to the size and color of the nodes and lines. Exactly 13 authors have loadings greater than 0.3, and six authors have principal loadings on the "patent analysis" factor. The factor is mainly named by the six authors. However, most of the 13 authors have secondary loadings on the specialty bibliometric evaluation factor. GuanJC and LiuYX have the third loadings on the scientometrics policy and mapping of science factors, respectively. Authors who load on multiple factors may bridge several research fields. These contents show the close relationship between patent analysis and bibliometrics.

As shown in Figs. 1 and 2 and Tables 4 and 5, the first-author ABCA and AKCA methods yield different structures of the IS field, although the two reveal many consistent specialties. The first-author AKCA method provides a less detailed and

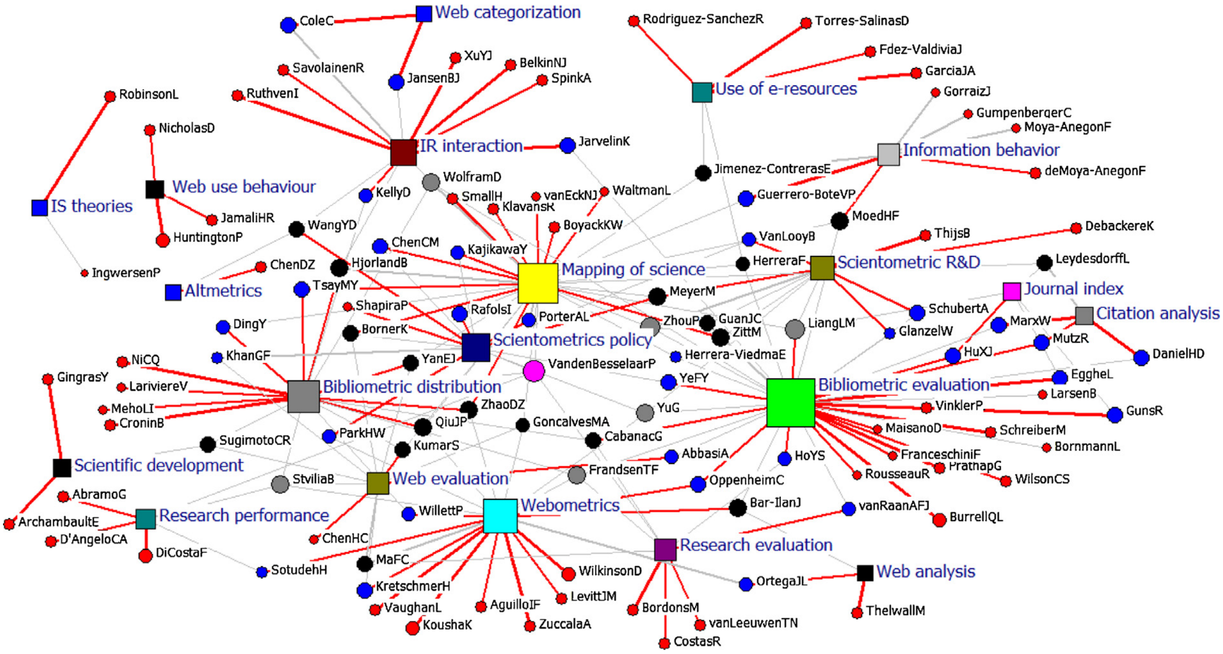

Fig. 4. Structure of the IS field in 2006–2015 as seen from the all-author ABCA.

uneven picture than the first-author ABCA method, with the former emphasizing a small number of general IS research areas and involving authors focused on two major specialties: bibliometric evaluation and IR interaction. The first-author ABCA method provides a detailed map of specializations as well as highly detailed information; under this method, authors are evenly distributed in these specialties and topics. Thus, the ABCA and AKCA methods have their respective strengths and emphases. The two methods offer significant contributions to the thorough understanding of the IS field. Multiple methods from different aspects need to be integrated to obtain a complete picture of the intellectual structure of a research field.

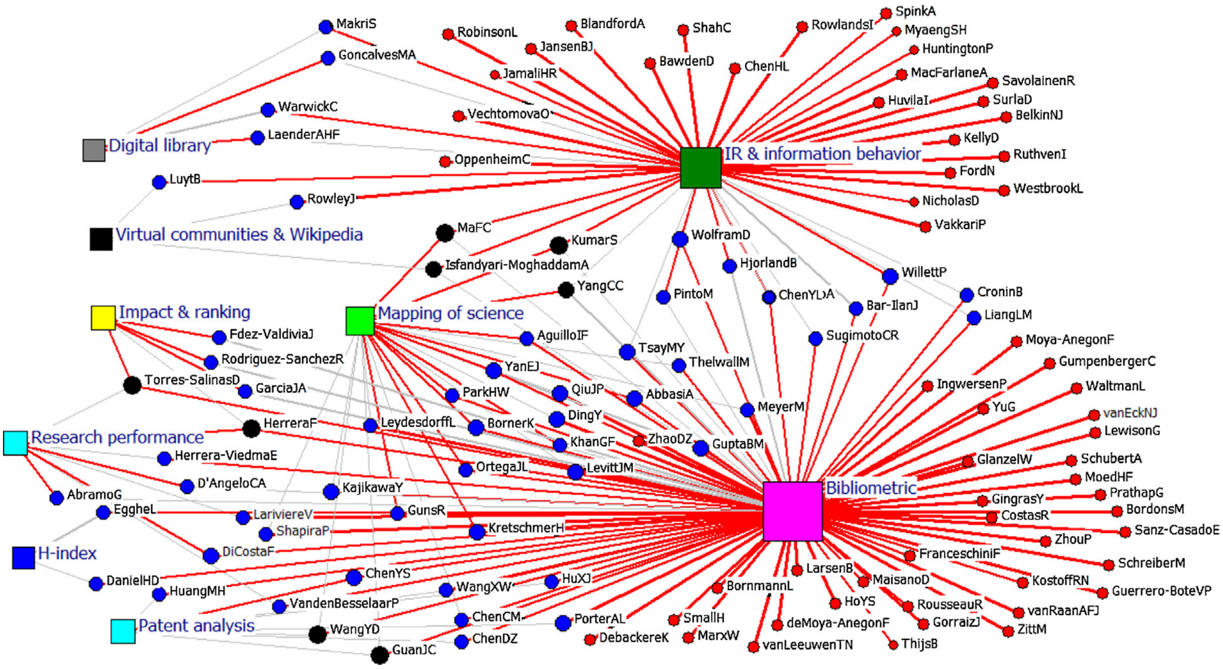

Fig. 5. Structure of the IS field in 2006–2015 as seen from the all-author AKCA.

Table 6
22-factor results from all-author ABCA of IS in 2006–2015.

Label	Size	Highest loading	Label	Size	Highest loading
bibliometric evaluation	19(36)	0.928	citation analysis	4(4)	0.87
Webometrics	12(20)	0.964	research performance	3(6)	0.925
mapping of science	12(30)	0.831	scientific development	2(3)	0.848
bibliometric distribution	13(19)	0.875	Undefined 1	0(0)	<0.3
IR interaction	7(12)	0.87	web use behavior	3(3)	0.889
scientometrics policy	9(16)	0.728	web categorization	2(2)	0.913
scientometric R&D	5(11)	0.806	web analysis	2(3)	0.819
research evaluation	4(9)	0.811	Altmetrics	1(2)	0.749
information behavior	7(7)	0.825	journal index	0(5)	0.539
use of e-resources	4(6)	0.871	Undefined 2	0(0)	<0.3
web evaluation	4(11)	0.605	IS theories	2(2)	0.826

4.4. Intellectual structure of IS based on all authors

Every author collaborates and shares references and keywords in multi-authored papers, although the contribution and credit contributed by each author is different. All-author coupling highlights non-first authors and clearly shows some cooperative groups. Figs. 4 and 5 visualize the 22-factor and 10-factor models, respectively, based on the all-author ABCA and AKCA. Tables 6 and 7 summarize these factors' labels, sizes, and distinctiveness. Highly similar results are observed between the all-author ABCA and AKCA and the first-author ABCA and AKCA. In Figs. 4 and 5, the two camps of the IS field are placed visibly apart, with the IR camp located toward the upper part of the map whereas the KDA camp is located toward the lower part. The connections (lines) within each camp are dense, whereas those between the two camps are remarkably sparse. Some authors build bridges between two camps, whereas most of them stay within their own camp. These large factors (specialties) in Fig. 4 are largely consistent with those in Fig. 5.

The all-author ABCA method has a significantly more complex structure (Fig. 4) and much dispersion compared with the all-author AKCA method (Fig. 5), which is consistent with the result of social network analysis (Table 2). The main reason is that references also represent the knowledge base in the case of all-author counting; references are dispersed while the keywords tend to be largely concentrated. We found that in the all-author AKCA method, 1686 words were used 15,406 times, while in all-author ABCA method, 44,483 references were used by 75,458 times. The red, blue, black, gray, and purple author nodes represent the authors who load on one, two, three, four, and five specialties, respectively. Many authors have loadings higher than 0.3 on more than one specialty, and many authors load highly on several specialties in Fig. 4. For example, the node "VandenBesselaar P" has loadings greater than 0.3 on five specialties, hence the purple color of the node; however, none of the specialties show loadings greater than 0.4. In Fig. 4, both IS theories and web use behavior are isolated from the other factors, thus indicating that the loading authors have unique contributions to these specialties and unique referencing behavior. The IS theories specialty has two authors: the high loadings of Robinson (0.826) and the low loadings of Ingwersen (0.301). However, Fig. 5 only has three colors in the author node, and the red nodes concentrate on two factors: 1) bibliometrics and 2) IR and information behavior. All authors have strong memberships (i.e., loadings > 0.3) in only one or two research areas, which correspond to red and blue nodes, respectively, except for eight authors (black) who belong to three research areas (factors). Fig. 4 shows many small topics that are greatly dispersed. The contents of these factors' labels overlap or are subordinated to a certain extent.

The specialties in Fig. 4 are more evenly distributed in size compared with those in Fig. 5, which shows significantly large and small factors. Eight factors have primary loadings from five or more authors. All four factors with primary loadings from more than 10 authors belong to the KDA camp in Fig. 4. In Fig. 5, most authors in Factors 3 (mapping of science), 4 (research performance), 5 (impact and ranking), 6 (patent analysis), and 10 (H-index) have fairly high loadings on Factor 1 (bibliometrics). Most authors in Factors 7 (digital library), 8 (information seeking behavior), and 9 (virtual communities and Wikipedia) also have loadings higher than 0.3 on Factor 2 (IR and information behavior). These specialties overlap, and two big camps are shown in Fig. 5. A possible reason is that the ABCA method is based on a bibliographic level, whereas the AKCA method has more levels (especially due to some general terms) and can reveal the various levels of intellectual structures.

The ABCA method visualizes more factors than the AKCA method (22 vs. 10, see Figs. 4 and 5), although two and one factors remain undefined in Figs. 4 and 5, respectively. Given that the relations within the ABCA and AKCA methods are, respectively, based on the same references and keywords, the all-author counting often expands the author's relationship because every

Table 7
10-factor results from all-author AKCA of IS in 2006–2015.

Label	Size	Highest loading	Label	Size	Highest loading
bibliometric	71(90)	0.926	patent analysis	0(8)	0.564
IR & information behavior	33(45)	0.928	digital library	2(4)	0.714
mapping of science	8(24)	0.721	Undefined	0(0)	<0.3
research performance	3(8)	0.75	virtual communities & wikipedia	0(4)	0.412
impact & ranking	3(5)	0.657	H-index	0(2)	0.473

author in a multi-authored paper only contributes partly to the references and keywords. We find that authors often tend to use the same keywords, but they have various references and often reference different documents from different fields. The labels in Figs. 4 and 5 are different because of changes in the sizes and scopes of the factors. In Fig. 5, bibliometrics is the most prominent factor with primary loadings from 70 authors, and corresponds to more than two big loadings in Fig. 4 (bibliometric distribution, scientometrics policy, scientometric R&D, etc.). IR and information behavior is the second most prominent specialty in Fig. 5 with primary loadings from 33 authors and comprises two closely related fields, namely IR and information behavior. This result reinforces the earlier observation that the ABCA method focuses on the details of a discipline, whereas the AKCA method emphasizes a more general discipline structure.

In conclusion, the ABCA method is based on references (i.e., a knowledge base), indirectly reflects the theme of an author's research, and shows details about disciplines and subspecialties. By contrast, the AKCA method is based on keywords that tend to directly denote general research areas. Consequently, the results from the AKCA method clearly indicate the major specialties of IS and provide a simple and clear overall structure of the IS field.

4.5. Comparison between the first and all-author coupling analyses

We compare the results in Figs. 1 and 4 with those in Figs. 2 and 5, as well as the results in Tables 4 and 6 with those in Tables 5 and 7. The intellectual structures revealed by the first- and all-author coupling analyses are largely the same, in general. The differences occur at the level of detailed substructures and in some small research areas.

First, 120 authors are used for each of the four author coupling matrices (first- and all-author ABCA and AKCA). On the basis of the data samples, we find that the first- and all-author bibliographic coupling matrices and the first- and all-author keyword coupling matrices comprise the same 65 and 66 authors, respectively. We can easily deduce that the matrix pairs do not share many common authors, with only about half of the selected authors overlapping between the first- and all-author ABCA and AKCA matrices. Some authors prefer to play the role of sole author, whereas others like to publish papers as co-authors. Some authors also tend to publish many papers without being a first author.

Second, as shown in Table 3, the factor model from the first-author counting has a better model fit than that from the all-author counting both in the ABCA (81.483 vs. 76.272) and the AKCA (83.128 vs. 81.43) methods while the differences between the observed and implied correlations are similar. The numbers of factors in the four coupling analyses are also different. First-author coupling analysis produces fewer factors in ABCA (16 VS. 22) but more factors in AKCA (13 VS. 10). This result may be mainly attributed to the fact that authors have different behaviors and habits when citing papers and using keywords. Different authors use different references when writing papers of the same topic; manuscripts are often written by one author instead of all co-authors. Compared with the first-author ABCA, the all-author ABCA considers larger amounts of information (i.e., papers and relations) and thus presents a more diverse author relationship. The all-author ABCA also tends to increase the intellectual diversity among authors, which might in turn reduce model fits by increasing the total variance that needs to be explained by a model. However, in the all-author AKCA, different authors tend to use the same words to express and label the common theme (i.e., they use the same keywords for the similarity papers) because professional vocabulary in one area is relatively fixed and recognized according to the assumptions of co-word analysis (He, 1999).

Third, two camps of IS are obvious in Figs. 1, 2, 4 and 5, the upper and bottom parts of which represent the IR camp and the KDA camp, respectively. By comparing the two camps in Tables 4 and 6 and those in Tables 5 and 7, we find that the KDA camp is more prominent in the all-author coupling analysis than in the first-author coupling analysis in terms of the number of big factors and the primary loading authors. For example, all four factors (the numbers of primary loading authors are greater than 10) belong to the KDA camp in the 22-factor results from the all-author ABCA. Factor bibliometrics is part of the KDA camp and is the biggest factor (the number of primary loading authors is 71) in the 10-factor results from the all-author AKCA. This result can be explained by the fact that in general, the KDA camp comprises papers with more authors, particularly prolific authors, than those comprising the IR camp. All-author coupling favors research groups with a large number of co-authors.

Fourth, all-author coupling provides a more comprehensive picture than first-author coupling. All-author co-citation analysis has been applied by Zhao and Strotmann (2008c); the meaning of all-author counting in author coupling (keywords) analysis is similar to all-author co-citation analysis. Subsequent authors in multi-authored papers may have contributed in different ways, possibly representing different levels of credit and accountability. Although often contributing less than the first author, various authors in a multi-authored paper in IS also tend to be in the same research field. All-author coupling highlights papers with non-first authors and clearly shows some cooperative groups. Several representative scholars have long been core members of certain teams as co-authors rather than as first authors. For example, Ingwersen P appears in the all-author AKCA and ABCA but not in the first-author AKCA and ABCA because this author published three first-author papers and nine papers total (i.e. all-author) according to our sample data. Thelwall M appears in all four coupling analyses but is obviously more prominent in the all-author coupling analyses than in the first-author coupling analyses because he published 27 first-author papers and 74 all-author papers. Rousseau R is not among the 120 authors in the first-author AKCA, as he published only 9 first-author papers and 58 all-author papers. We need to use both first- and all-author coupling to examine the overall intellectual structure of research fields, particularly because all-author coupling offers a broad overview of disciplinary structures.

In the comparison of the ABCA and AKCA maps, both for first- and all-author counting, it is interesting to add some comparisons of individuals, particularly of individuals that change and end up associated with different factors in different maps. These changes happen because we mainly used authors to represent the field or topic of a discipline rather than revealing the research field of specific authors. On the one side, some authors are different in the first- and all-author maps because of the differences in the number of published papers in the first and all author counting. Some authors are also different in the ABCA and AKCA maps because of the different of keyword and bibliographic coupling frequencies. For example, Moed HF appears both in the all-author ABCA and AKCA maps, but not in the first-author ABCA and AKCA maps; Braun T appears in the Bibliometric evaluation of the first-author ABCA map (Fig. 1), but not in the other three maps.

On the other side, some authors change their place in these maps. Take Small H, Waltman L, and van Eck NJ as examples. According to a general understanding, all three authors have focused both on Bibliometric and Mapping of science for 2006–2015, but we can find some significant departures in this representation. In the first-author ABCA map (Fig. 1), Small has a principal loading (0.79) in Mapping of science and second loading (0.342) in Citation content analysis; Waltman has a principal loading (0.761) in Bibliometric evaluation and second loading (0.425) in Mapping of science; van Eck has only one loading of more than 0.3, for Mapping of science (0.859). In the first-author AKCA (Fig. 2), Small, Waltman and van Eck have principal loadings (0.698, 0.737, 0.609, respectively) in Mapping of science and a second loading (0.49, 0.384, 0.492, respectively) in Bibliometric evaluation. However, because we consider the non-first authors papers in the all authors counting, in the all-author ABCA map (Fig. 4), all three authors have principal loadings (0.831, 0.538, 0.541, respectively) and are linked exclusively to Mapping of science, while in the all-author AKCA map (Fig. 5), all three authors have principal loadings (0.839, 0.853, 0.849, respectively) and are linked exclusively to Bibliometric. In our opinion, the main reason is that the relatedness between the authors is measured differently: the relationships within the ABCA and AKCA methods are based, respectively, on the same references and keywords. For example, in the all-author ABCA map (Fig. 4), Small, Waltman and van Eck have principal loadings on Mapping of science because these authors in the factor have many of the same references and share the topic of science mapping, although they have their second highest loadings (0.127,0.285, 0.274, respectively, and less than 0.3) in Bibliometric evaluation. In the all-author AKCA map (Fig. 5), Small, Waltman and van Eck have principal loadings on Bibliometric because they have many of the same words and share the topic of bibliometrics, although they have loadings (0.252, 0.002, 0.026, respectively) in Mapping of science.

Overall, the first- and all-author coupling analyses produce different results, although in fields such as IS, co-authorship levels are relatively low (Zhao & Strotmann, 2008c). First-author coupling analysis visualizes researchers with significant achievements, whereas all-author coupling analysis considers all the contributions of researchers regardless of their roles in research teams (Zhao & Strotmann, 2011). Collaboration has become increasingly popular in scientific research in the "big sciences" era. Fundamental limitations emerge when only first authors are considered because doing so disregards the contributions of researchers who are not first authors. In many cases, the first author is not always the one who contributes the most to an article. In fact, papers are often written by corresponding authors instead of first authors. Thus, the traditional first-author coupling analysis may not be an adequate alternative to all-author coupling analysis.

4.6. Comparison between IS in 1996–2005 and in 2006–2015 using ABCA

Zhao and Strotmann (2008b) studied the IS field between 1996 and 2005 by introducing first-author ABCA (Table 8). We use 10 year maps to verify the feasibility of ABCA with long time windows because different time windows have some influence on others methods (e.g. Direct citation analysis). We visualized the same field between 2006–2015 by using the same method, the same sample journals, and the same number of representative authors. However, Zhao and Strotmann (2008b) split the 10 years into two five-year periods (i.e., 1996–2000 and 2001–2005) and mapped the corresponding structures. Zhao and Strotmann (2008a, 2008b, 2014) also used the same time slice for ABCA in some of their previous studies. This approach is reasonable because five-year periods offer a more detailed view of the development of the IS field than longer time periods. The results can be conveniently compared with the two consecutive five-year periods. However, ABCA may have more relations between authors and generate better analysis results for longer time periods than for five-year periods. JCR 2014 includes cited half-life data for 66 of 85 LIS journals, of which 59 journals have a cited half-life of more than 5 years. So, our use of a 10-year period leads to good results and visualization effects. We believed that, to a certain extent, the two data sets are comparable, although 5 year maps would have been much more comparable.

We compare the results from the first-author ABCA of IS in 1996–2005 and 2006–2015 and determine the evolution of IS from the first to the second decade of the World Wide Web. The overall structure is relatively stable, whereas some local subareas have undergone minimal restructuring. IS has continuously evolved mainly because of the rapid development of information technologies and Internet applications.

The two camps in the IS field show obvious differences. The KDA camp became remarkably prominent during the Web revolution. Specifically, two factors with the largest size of author primary loading belong to the IR camp for the periods of 1996–2000 and 2001–2005 and then to the KDA camp for the period of 2006–2015 (bibliometric evaluation and science mapping, i.e., two specialties that account for about half of the number of IS authors). Moreover, the patent analysis field emerges in the KDA camp as a completely new specialty. Patents establish the primacy of an invention or innovation. Patent documents are important components of the innovation system and serve as a direct reflection of innovation and technological levels. Patent analysis focuses on patent bibliometrics.

Table 8
Results from first-author ABCA of IS in 1996–2005 (Zhao & Strotmann, 2008b), 2006–2010 (Zhao & Strotmann, 2014), and 2006–2015 (present study).

1996–2000			2001–2005			2006–2010			2006–2015		
Label	Size	Highest loading	Label	Size	Highest loading	Label	Size	Highest loading	Label	Size	Highest loading
IR interaction	33	0.95	IR interaction	17	0.84	h-index (bibliometric distributions;research evaluation)	25	1.024	Bibliometric evaluation	38(54)	0.95
IR systems	20	0.9	Information behavior	16	0.9	Information behavior	16	0.914	Mapping of science	22(46)	0.89
Mapping of science	16	0.75	Webometrics	15	0.95	Mapping of science	15	0.886	IR interaction	20(31)	0.89
Collaboration	12	0.89	Children's Web search behavior	12	0.98	Webometrics	14	0.897	Webometrics	6(14)	0.94
Scholarly communication and Web	9	0.86	IR systems	11	0.91	Relevance	11	0.736	Patent analysis	6(14)	0.9
Bibliometric models and distributions	7	0.8	Mapping of Science	11	0.85	IR systems	9	0.914	Scientometrics policy	6(17)	0.79
Scientometrics	6	0.71	Scientometrics	11	0.85	IS theories & foundations	9	0.869	Citation content analysis	5(14)	0.75
OPAC	5	0.74	Image retrieval	10	0.9	UD (open access & bibliometrics)	8	0.600	IR systems	6(9)	0.79
Undefined 1	6	0.54	Bibliometric models and distributions	7	0.9	Journal editors	8	0.963	Open access	3(3)	0.68
Undefined 2	4	0.51	E-resources in science communication	5	0.72	Virtual communities	6	0.877	IS theories	1(7)	0.56
Undefined 3	2	0.46	Undefined	5	0.52	Citation content & context analysis	6	0.837	Collaboration analysis	1(5)	0.56
						Web searching	6	0.778	Web text analysis	2(2)	0.7
						Use of e-journals & other e-resources	6	0.777	Web use behavior	2(2)	0.79
						Patenting and patent analysis	6	0.744	Virtual reference	2(3)	0.53
						Image representation & retrieval	4	0.894	Undefined 1	0(3)	0.3
						UD	1	0.511	Undefined 2	0(3)	0.49

The main reason for the growth of the KDA camp is the constant increase in the number of published papers and scholars, which in turn increases the number of high-yield authors belonging to the KDA camp. We found the growth in some journals and not others is related to the relative growth of KDA and relative decline of IR. The amount of articles increased from 150 in 2006 to 338 in 2014 in Scientometrics, while the amount of articles decreased from 101 in 2006 to 89 in 2013 and 52 in 2014 in Information Processing & Management. Other journals remain relatively stable, although there are small fluctuations. Besides, we found KDA (especially bibliometrics) is a big part in IS in our research and others mapping, due to some special bibliometric journals publish many paper, and have more prolific authors. This condition is the result of the expansion of research in the KDA camp. Quantitative studies have become a trend and continue to prove valuable in the new environment. KDA focuses on quantitative studies of science and technology, which are largely driven by information technology and Internet technologies (Zhao & Strotmann, 2014). Various evaluation indicators and methods (H-index, eigenfactor, SNIP, SJR, etc.) are continuously introduced and improved. New research areas (patent analysis, altmetrics, etc.) are seriously considered in KDA. As for the IR camp, it has become relatively small after the internal restructuring it has undergone over the years, although it still receives a number of new Web-related topics, such as Web use behavior. Specifically, IR systems shrunk from 1996–2005 to 2006–2015. The hard IR research includes IR systems and parts of image representation and retrieval. Scholars in very technical fields pay attention to hard IR research and its sub-topics. Scholars in the IS field have transferred to soft IR because of their interest in user–system interaction, information behavior, relevance, etc. In addition, our result (2006–2015) is largely consistent with the IS field 2006–2010 in Zhao and Strotmann (2014), because of the time period overlap. The overlap, to some extent, validated our findings' reliability. However, we have some new findings not in Zhao and Strotmann (2014): Patent analysis and Mapping of science are more prominent; Scientometrics as part of science policy is emerging.

Internal change has occurred in the two camps of the IS field. We display some evidence of internal restructuring in the two camps during this decade. First, the OPAC topic in 1996–2000 disappeared and was no longer an active research topic in 2006–2015. Moreover, the IR systems field is no longer among the specialties that significantly influence research in the IR camp. Image retrieval is incorporated into IR interaction and is no longer a separate field. E-resources in science communication has been split into open access and Web text analysis. Bibliometric models and distributions is divided into two dependent parts: citation content analysis and collaboration analysis. Children's Web search behavior in 2001–2005 was replaced by Web use behavior in 2006–2015. Information behavior in 2001–2005 emerged in IR interaction in 2006–2015. The scientometrics field remains unchanged in terms of the size and nature of research, and its topics focus on science and technology policy and management. Second, in 2006–2015, patent analysis and virtual reference emerged in the new environment. Bibliometric evaluation has become the most prominent research area, accounting for 32% of IS, with the h-index attracting many scholars in the field. Mapping of science is likewise prominent and ranks second among all the factors. Thus, this research area is an important part of recent research in IS. Open access and virtual reference have become independent research topics because of the pervasive influence of the Internet. The Web is changing the way that people communicate information and utilize e-resources both in everyday life and in science.

5. Conclusion

This article introduced the AKCA method for analyzing the intellectual structure of a field and compared it with the ABCA method, particularly in terms of first- and all-author coupling. We applied this new methodology to the field of IS (2006–2015).

5.1. Author keyword/bibliographic coupling analysis

The factor models from the AKCA matrices show a significantly better fit than those from the ABCA matrices in terms of first- and all-author counting. The structure of IS in 2006–2015, as obtained with the ABCA method, is largely consistent with that obtained with the AKCA method, although some differences between the two sets of results can also be observed. The ABCA and AKCA methods have their respective strengths and emphases. First, the ABCA method visualizes more factors than the AKCA method. Moreover, the AKCA method presents a less detailed picture of a few general research areas of IS, whereas the ABCA method provides a detailed map of specializations and information and facilitates the even distribution of authors in these specialties. Second, the specialties and topics in the ABCA and AKCA methods have different sizes, scopes, and emphases at the micro level. Third, the KDA camp and IR camp based on the AKCA method have fewer contacts and connections compared with those based on the ABCA method. The relation within the ABCA method is based on the same references (knowledge base), whereas that within the AKCA method is based on the same keywords. In the ABCA method, the relationships between authors are broad, indirect, and fixed at the document level. In the AKCA method, the relationships between authors are narrow and direct and have different levels of meaning. Although the AKCA method is more complex and expensive to perform than the ABCA method, it is advantageous when applied to factor labeling. Furthermore, although the AKCA method cannot replace the ABCA method, the method works reasonably well and has a place in the repertoire of methods to conduct structural studies.

5.2. Intellectual structure based on first- and all-author coupling analyses

The intellectual structures revealed by the first- and all-author coupling analyses are largely the same but also show significant detailed differences. Unlike the all-author coupling analysis, the first-author coupling analysis produces a factor model with a good model fit that is simple to interpret. First-author coupling favors authors who tend to work alone, whereas all-author coupling reveals collaborative author clusters. All-author coupling considers all contributions of researchers regardless of their roles in research teams and thus provides a more comprehensive picture than first-author coupling. Thus, with the number of authors per article and multi-authored papers are continuously increasing, a complete view of the field structure of IS may require both first- and all-author coupling analyses.

5.3. Information science (2006–2015)

The overall structure of IS in 2006–2015 was relatively stable, whereas some local subareas showed minimal restructuring. IS has been continuously evolving because of the rapid development of internet technologies between 1996–2005 and 2006–2015. The KDA camp, in particular, was very active, becoming prominent during the Web revolution. The patent analysis field emerged strongly in the KDA camp, and the areas of mapping of science and bibliometric evaluation underwent substantial growth. As for the IR camp, it underwent several instances of internal restructuring during the second decade of the Web. The IR camp, especially hard IR research, further declined and became significantly small, although it continues to receive new Web-related topics, such as open access and virtual reference.

5.4. Research outlook

Although the study provides interesting findings in the structure of IS and shows that the AKCA method provides significant insights into intellectual structures, some questions must be addressed in future studies. First, choosing representative authors is very important, although no perfect selection criteria are available to determine "core authors" in some similar studies. A total of 120 authors from 12 journals were used in this study to represent the IS field. However, the following questions emerge. Can these 120 authors represent the whole IS field? Why should the number of authors be 120 and not 100 or 150? Furthermore, the top 120 authors were selected on the basis of the number of publications and average coupling frequencies. However, the reasonability, validity, and appropriateness of the method require further investigation. The field of bibliometrics shows certain advantages in terms of the number of prolific authors and co-authors as well as coupling frequency. Bibliometrics is a very prominent field in IS, as found in this study and in other works. Thus, numerous questions about how well mapping reflects the actual situation in the IS field must be resolved. Second, the relation within the AKCA method is based on the same keywords. However, some papers have no keywords. For example, many records used in this study have no DE and ID in JASIST. The idea of extracting terms from titles, abstracts, or full texts must thus be explored to obtain a comprehensive view of a certain field, since keywords have some inherent disadvantage properties. Furthermore, the contextual units within which key terms occur must be confirmed. Semantic analysis needs to be employed automatically to enhance processing efficiency and improve the synonym and polysemy phenomena. Labeling factors exactly and conveniently is difficult because of the need to synthesize common themes in articles by different authors. Finally, future studies should analyze other disciplines and other databases (e.g., Scopus) in a similar way, in order to examine thoroughly the validity of AKCA and its effectiveness in studying intellectual structures.

Author contributions

Conceived and designed the analysis: Siluo Yang, Dietmar Wolfram.
Collected the data: Siluo Yang, Ruizhen Han.
Contributed data or analysis tools: Siluo Yang, Ruizhen Han, Yuehua Zhao.
Performed the analysis: Siluo Yang.
Wrote the paper: Siluo Yang.
Other contribution: Dietmar Wolfram.

Acknowledgments

We wish to thank the two anonymous referees for their important insightful comments and suggestions. This research is funded by A Foundation for the Author of National Excellent Doctoral Dissertation of PR China (2014094).

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