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Intellectual structure of knowledge in iMetrics: A co-word analysis

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A B S T R A C T

As an iMetrics technique, co-word analysis is used to describe the status of various subject areas, however, iMetrics itself is not examined by a co-word analysis. For the purpose of using co-word analysis, this study tries to investigate the intellectual structure of iMetrics during the period of 1978 to 2014. The research data are retrieved from two core journals on iMetrics research (*Scientometrics*, and *Journal of Informetrics*) and relevant articles in six journals publishing iMetrics studies. Application of hierarchical clustering led to the formation of 11 clusters representing the intellectual structure of iMetrics, including "Scientometric Databases and Indicators," "Citation Analysis," "Sociology of Science," "Issues Related to Rankings of Universities, Journals, etc.," "Information Visualization and Retrieval," "Mapping Intellectual Structure of Science," "Webometrics," "Industry–University–Government Relations," "Technometrics (Innovation and Patents), "Scientific Collaboration in Universities", and "Basics of Network Analysis." Furthermore, a two-dimensional map and a strategic diagram are drawn to clarify the structure, maturity, and cohesion of clusters.

1. Introduction

Metric studies have been developed as a subsidiary branch of Library and Information Science over time. Various concepts of the field, such as bibliometrics, scientometrics, informetrics, webometrics, and technometrics are found in LIS journals. As proposed by Milojevic and Leydesdorff (2013), these concepts have similar goals and methods, and can be grouped under a research subset titled *information Metrics* or *iMetrics*. Using co-citation, bibliographic coupling, and co-word methods for exploring research topics in LIS, Chang, Huang, and Lin (2015) found that iMetrics was the most significant topic in LIS subsets. As an independent trend, iMetrics is not only emerging, but is also evolving into its socio-cognitive nature (Milojevic & Leydesdorff, 2013). By the application of common techniques in iMetrics, one can collect and evaluate data onto research trends and researcher status in different disciplines while evaluating research output concurrently (Hunter, 2009; Stidham, Sauder, & Higgins, 2012; Webster, 2011; Weightman & Butler, 2012; Zyoud, Al-Jabi, & Sweileh, 2014). Due to its applications, iMetrics is also employed by researchers in other disciplines.

Considering the gradual emergence and development of iMetrics, a comprehensive macro image of research on iMetrics should be drawn, and its scientific development needs to be explored, in order to enquire into its advancement in a temporal

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continuum. One of the techniques employed for analyzing the knowledge structure of diverse fields is studying the relation between words used in various parts of a document, including the title, abstract, keywords, etc. This technique is called "co-word" analysis, and is a well-established and effective approach, that can show the intellectual structure of a research field (Ronda-Pupo & Guerras-Martin, 2012). It is an approach used for establishing a subject similarity between two documents (Rokaya, Atlam, Fuketa, Dorji, & Aoe, 2008). Co-word analysis presumes that a group of aggregated keywords could indicate underlying themes, and that co-occurrences of keywords could show the associations with the underlying themes (Hu & Zhang, 2015). By employing co-word analysis, one can determine the major topics in a field, in addition to its semantic structure and evolution over the time. In co-word analysis, it is supposed that frequent words have more meaning of an effect on a field than the less frequent ones. It help in determining both the emerging and the developed subject clusters to suggest the research path in the future (Lee & Su, 2010).

The frequency of word occurrence is a principal measure in content analysis. This measure is used for exploring the major topics in a research field by giving attention to highly frequent words. In other words, the frequency of a given word is an indicator of the importance of the word and its notion. Keywords have the potential for effectively describing the contents of a paper. If two keywords occur simultaneously in a paper, they have a semantic relationship (co-word/co-occurrence). The higher co-occurrence frequency of two keywords implies the more correlative they are (Liu, Hu, & Wang, 2012).

Like other co-occurrence analyses, particularly that of co-citation, co-word analysis is one of the fundamental methods for demonstrating the relationship among concepts. It is used to determine research frontiers in academic disciplines and explore knowledge structures in various research fields (Hu, Hu, Deng, & Liu, 2013; Ravikumar, Agrahari, & Singh, 2015; Stegmann & Grohmann 2003; Xie, 2015). By studying and analyzing the co-occurrence of keywords in the papers of a certain field, one can draw an instant picture of interesting topics within the field (Ding, Chowdhury, & Foo, 2001). In other words, there are collections of concepts in each scientific and technological field that build its knowledge structure. These concepts are expressed as keywords that are made for describing and naming them. Exploring concepts and the relationship between them by means of word relations in documents eases the creation of a scientific map.

As stated earlier, co-word analysis is one of the commonest approaches to iMetrics which allows us to reveal the emerging thematic clusters and the changes of traditional thematic clusters in order to forecast the path of coming researches (Lee & Su, 2010), and to study it's conceptual and semantic relations (Leydesdorff & Welbers, 2011). In addition, the intellectual structure of scientific domains can be examined as forming a cluster via clustering techniques and multidimensional scaling (Cho, 2014; Yan, Lee, & Lee, 2015). The data relating to co-word analysis as well as the data relating to other co-occurrence analyses (such as co-citation and co-authorship) have the potential of being analyzed using multidimensional scaling, network and cluster analysis and to show the structure of knowledge in a given field (Allendoerfer, 2008).

Finally, the use of novel technologies in network analysis can reveal the ruling relationships in co-word analysis and deeply examine these complex relationships and depict the structure of knowledge in a specific field. Studying the knowledge structure can be fruitful for both researchers and science policymakers. Although co-word analysis is a kind of iMetrics technique, iMetrics itself is not examined through co-word analysis using relatively complete records. For this purpose, i.e. using co-word analysis, this study aims at investigating the intellectual structure of iMetrics during the period from 1978 to 2014. This paper tries to answer the following questions:

1. Can the intellectual structure of iMetrics be visualized and represented using hierarchical clustering?
2. Can the intellectual structure of iMetrics be visualized and represented using multidimensional scaling?
3. How are topics and clusters of iMetrics represented by the strategic diagram in terms of maturity and development?

2. Literature review

Since its introduction by Callon, Courtial, Turner, and Bauin (1983), numerous researchers have used co-word analysis to study various fields. Some of these fields include information system management (Culnan, 1986), information retrieval (Ding et al., 2001), robot technology (Lee & Jeong, 2008), aerosol research (Xie, Zhang, & Ho, 2008), obstructive sleep apnea (Huang, 2009), distance education (Ritzhaupt, Stewart, Smith, & Barron, 2010), solid waste (Fu, Ho, Sui, & Li, 2010), risk assessment (Mao, Wang, & Ho, 2010), global climate change (Li, Wang, & Ho, 2011), stem cells research (An, & Wu, 2011), library and information science (Astrom, 2002; Hu et al., 2013; Sugimoto, Li, Russell, Finlay, & Ding, 2011; Wang, Zhang, & Wei, 2011; Zong et al., 2013), economics (Vaughan, Yang, & Tang, 2012), consumer behavior research (Muñoz-Leiva, Viedma-del-Jesús, Sánchez-Fernández, & López-Herrera, 2012), digital libraries (Dong, 2009; Liu et al., 2012), competitive intelligence (Xiang, & Qiu, 2012), knowledge management (Sedighi, & Jalalimanesh, 2014), engineering (Wu, & Leu, 2014), human–computer interaction (Liu et al., 2014), sociology of science (Dehdarirad, Villarroya, & Barrios, 2014), domestic knowledge discovery (Wang, Liu, & Sheng, 2014), cancer research (Xie, 2015), creativity (Zhang, Zhang, Yu, & Zhao, 2015), social networks in marketing (Wang, Zhao, & Wang, 2015b), computer sciences (Hu & Zhang, 2015; Wang, Zhang, & Liu, 2015a), Internet of Things (Yan et al., 2015) and computer games (Melcer et al., 2015).

In spite of numerous research conducted by co-word analysis to diverse scientific fields, few have considered iMetrics and related fields on their own. In one of the first studies of its kind, Courtial (1994) studied iMetrics (scientometrics) by using co-word analysis for 595 papers published between 1988 and 1993. The results revealed some clusters including, among others, "databases", "citation analysis", "author productivity", "scientific evaluation", "law of scattering", "bibliometrics", "co-word analysis", and "journal impact factor". The results also showed that during 1988–1990, iMetrics developed based on “databases”, “research evaluation”, and “citation analysis”, whereas during 1992–1993, it focused on one common goal: “scientific research evaluation”. Courtial concluded that iMetrics had attained content and dynamic stability. Janssens, Leta, Glänzel, and De Moor (2006) carried out a co-word study on 938 selected papers published in five library and information science journals between 2002 and 2004. By hierarchical clustering, they discovered six subject clusters including two clusters in bibliometrics, and one cluster in information retrieval, webometrics, patent, as well as the generalities in each. The clusters related to webometrics and patents were smaller than the others. In a relatively recent study, Ravikumar et al. (2015) mapped the intellectual structure of the *Scientometrics* journal through co-word analysis. The authors examined the complete text of all 959 selected papers published in the journal during 2005–2010. They explored subject trends and patterns of the journal by measuring the communicative power of selected keywords. The co-word analysis was based on 240 keywords with at least 10 frequencies. They used hierarchical clustering, multidimensional scaling, and social network analysis, and discovered that the papers published were on subjects some of which were stable while others were changing. In other words, some subjects such as citation analysis, productivity, and bibliometric analysis were stable and lasting, whereas some other subjects, such as knowledge mapping and Baysian analysis were newly-emerging.

Sedighi (2016) used word co-occurrence analysis method in the mapping of the scientific fields with emphasis on the field of Informetrics. The co-word occurrence maps showed that concepts such as “information science”, “library”, “bibliometric analysis”, “innovation” and “text mining” were amongst the commonest topics in the field of informetrics.

As it stands, though a few studies have been conducted using the co-word method on iMetrics research, yet in some cases, such as Courtial (1994) a long time has elapsed since the research and in that time, new and emerging issues have found their way to the body of iMetrics; in some cases, such as Janssens et al. (2006) the major emphasis was on the Library and Information Science (LIS), and iMetrics was not exactly seen as a subset of LIS; and in some cases such as Ravikumar et al. (2015) only a few articles (959 articles) have been studied out of a specific journal.

Furthermore, several other works focused on other methods in iMetrics papers. Egghe (2012), for instance, studied the papers published in 2007–2012 in the *Journal of Informetrics*. Content analysis of these papers revealed that the subjects of more than half of the papers were citation analysis and/or h-indices, miscellaneous topics, and visualization. Wang, Qiu, and Yu (2012) examined the cross-citation relationship among important authors in the scientometric field. Erfanmanesh, Rohani, and Abrizah (2012) studied the co-authorship network of the field in 3125 papers published in *Scientometrics* during 1980–2012. Dutt, Garg, and Bali (2003) studied 1137 papers published in the first 50 volumes of *Scientometrics* during 1978–2001. In a different study in iMetrics, Leydesdorff, Bornmann, Marx, and Milojevic (2014) studied the historical origins of iMetrics by applying Referenced Publication Years Spectroscopy (RPYS). In an interesting study, Vinkler (2017) investigated the publication performances of 30 iMetrics experts. Abrizah et al. (2014) explored the successful authors in the field of informetrics by studying 5417 papers published in a 64-year time period (1948–2012).

Given the above literature, numerous researches have focused on iMetrics, but there is a criticism relating to these researches which is associated with the research strategy and their primary records: the records upon which the conclusions were obtained suffered from a lack of enough comprehensiveness and accuracy. For instance, some researchers worked based on precise and frequent keywords of iMetrics and they searched and retrieved primary records based on them. Thus evidently, numerous studies in the field of iMetrics not having used those keywords, may be disregarded. Some others including Bharvi, Garg, and Bali (2003), Chen, Borner, and Fang (2012), Dutt et al. (2003), Egghe, Goovaerts, and Kretschmer (2007), Erfanmanesh et al. (2012), Hou, Kretschmer, and Liu (2008), Schoepflin and Glänzel (2001) and Ding, Liying, and Qing (2013) based their work only on articles published in the core journal of this field (journal of Scientometrics), that is, although the examined population is relevant enough, the issue of lacking comprehensiveness still exists: various articles in the field of iMetrics that were published in other important journals of this field have been excluded.

However, in spite of the fact that most studies on the iMetrics are seriously limited in terms of sample size, we should not forget that the sample size in few studies such as Abrizah et al. (2014) and Leydesdorff et al. (2014), derived from Milojevic and Leydesdorff (2013), were obtained from a systematic and relatively complete method. In this research, it has been tried to examine the entire articles in the field of iMetrics. Thus, what differentiates this study from most of the previous ones is the research strategy employed to include the primary records. Furthermore, both types of keywords (author keywords and Keywords Plus) are incorporated into the co-word analysis. Moreover, the other major difference is in the analysis trying to analyze the intellectual structure of iMetrics and provides an updated and comprehensive picture of research in this area.

3. Methodology

This paper employed both co-word analysis and social networking analysis. The population comprised iMetrics papers indexed in the Web of Science (WoS) between 1978 and 2014. As stated above, in the previious studies on fields such as bibliometrics, informetrics, webometrics, and iMetrics in general, the absence of a justified and appropriate statistical population can be felt. Selection of primary data is essential in every iMetrics study on the grounds that it directly influences consequent results and conclusions. Considering this point, following the approach introduced by Milojevic and Leydesdorff (2013), the statistical population of this research included all papers published in *Scientometrics* and *Journal of Informetrics*, in addition to iMetrics papers published in six journals including: *1. Information Processing and Management, 2. Journal of American Society for Information Science and Technology (JASIST), 3. Journal of Documentation, 4. Journal of Information Science,*

Table 1
The frequency of iMetrics papers published in the studied journals.

Journal name	No. of all document types	No. of articles and proceedings	No. of iMetrics articles (after applying reference and keyword criteria)		
			Articles based on keyword search	Articles based on reference criterion	No. of iMetrics articles
Scientometrics	4003	3556	–		3556
JASIST	5194	3503	758	87	845
Journal of Informetrics	510	463	–		463
Research Policy	2680	2248	327	26	353
Research Evaluation	429	384	213	18	231
Journal of Information Science	1941	1434	146	28	174
Information Processing and Management	2965	1968	145	43	188
Journal of Documentation	2714	866	91	43	134
Total	20,436	14,422	–		5944

5. Research Evaluation, and *6. Research Policy*. The reason for choosing these journals is that they publish most of the papers in the field of iMetrics (Milojevic & Leydesdorff, 2013).

3.1. Data collection

A relatively comprehensive method introduced by Milojevic and Leydesdorff (2013) was employed for data collection in this study. Initially, all documents in the WoS that were published in the eight aforementioned journals were extracted. Then, items labeled under "article" or "proceedings" were chosen. The papers irrelevant to iMetrics in the aforementioned six journals were excluded. All papers published in *Scientometrics* and the *Journal of Informetrics* were included. Furthermore, every paper published in *Journal of American Society for Information Science and Technology (JASIST), Information Processing and Management, Journal of Documentation, Journal of Information Science, Research Evaluation*, and *Research Policy* which cited one of the papers published in *Scientometrics* or *Journal of Informetrics* were included. In other words, citation to papers published in *Scientometrics* and *Journal of Informetrics* as core journals of iMetrics was the criterion for separating the papers published in the other six journals in iMetrics from those of in non-iMetrics. Record screening was done using isi.exe software.

There were cases in which some of the iMetrics papers published in these journals had no citation to *Scientometrics* or the *Journal of Informetrics*. For retrieving such papers, the following search strategy was developed based on several highly frequent keywords, which have been extracted from previous works:

> TITLE= ("informetric*" OR "bibliometric*" OR "scientometric*" OR "webometric*" OR "citation*" OR "cite"OR "*citation" OR "indicator*" OR "productivity" OR "mapping" OR "h-index" OR "h index" OR "Hirsch index" OR "*index" OR "co-autho*" OR "coautho*" OR "impact factor*" OR "link analys*" OR "link structure" OR "patent analys*" OR "Zipf*" OR "Bradford*" OR "Lotka*" OR "collaboration network*" OR "scientific collaborat*")

Finally, considering the attempt in achieving a comprehensive statistical population, 5944 papers in iMetrics were recognized and analyzed. As indicated in Table 1, most of these papers were published in the journals of *Scientometrics, JASIST*, and *Informetrics*.

3.2. Data analysis

After retrieving 5944 records in the iMetrics and integrating data files based on the research aim, the structure of knowledge in the field was studied using co-word analysis. In the first step, keywords of the retrieved papers were studied. Records indexed in the Web of Science have two keyword types: author keywords and Keywords Plus. The former is given by the author, and the latter by a special automated program that extracts keywords from the titles of a paper's reference list (Zhang et al., 2016). Garfield (1990) believed that these keywords had the potential of providing the deeper and more extended content of a paper. Conversely, Zhang et al. (2016) claimed that Keywords Plus were broader than those assigned by the authors. Consequently, in some studies on keywords for co-word and bibliographic analyses, both keyword categories have been employed (Fu et al., 2010; Mao et al., 2010; Xie et al., 2008; Zhang et al., 2016; Huang, 2009; Huang, Ao, & Ho, 2008).

A primary analysis indicated that most papers published between the years 1987–1990 in the retrieved journals lacked an abstract or keywords. Since 1991, several papers have looked different: papers published in *Scientometrics* from 1991 to 2009 lacked any author keywords, and had Keywords Plus assigning them keywords in many cases. Since 2010, both keyword categories have been included in these papers. The *Journal of Informetrics*, being a recent one (since 2007), included both keyword categories in its papers. *JASIST* lacked author-assigned keywords, but Plus ones from 2007 to 2011. Some papers of this journal have included author keywords as well as Keywords Plus since 1998. The other journals had relatively similar states from this viewpoint.

Table 2
Ranking keywords based on their frequencies.

Rank	Keyword	Frequency	Rank	Keyword	Frequency
1	Impact Indicators	1430	16	Patterns	256
2	Citation Analysis	1135	17	Universities	251
3	Scientific Collaboration	627	18	Co-Citation Analysis	224
4	H-Index	579	19	Index	217
5	Bibliometric Analysis	541	20	Model	216
6	Journals	515	21	Information	209
7	Research Performance	496	22	Ranking	206
8	Productivity	450	23	Scholarly Communication	198
9	Publication Analysis	405	24	Research and Development	190
10	Innovation	391	25	Web	163
11	Impact Factor	389	26	Quality Assessment	158
12	Technology	278	27	Mapping	147
13	Networks	277	28	Co-Word Analysis	143
14	Patents	266	29	Information Science	141
15	Co-Authorship Networks	260	30	Economics	136

In total, a primary analysis revealed that, of 5924 studied records, 4567 had at least one keyword category and 1377 had none. Thus, co-word analysis was constrained to these records. Both keyword categories were included in the co-word analysis in order to build a complete structure of research subjects and trends in iMetrics. In a second step, all author keywords and keywords Plus were merged into one file. 6532 individual keywords were repeated 29,239 times. On average, each paper included six author and/or Plus keywords. The keywords required editing to show their synonyms. Five experts on the field reviewed the keywords in a process that comprised editing, integrating, deleting, and mending. After conducting some tests, and based on Bradford's law, the keywords with a frequency of 20 were included in the final analysis. It is worth mentioning that in different co-word studies, different thresholds are used for the highly frequent keywords included in the final analysis. For instance, Liu et al. (2012) limited their analysis to 66 highly frequent keywords that comprised approximately 55% of the keywords. Hu et al. (2013) limited their analysis to 181 keywords, comprising 29% of the total keywords. By defining a threshold value of ≥ 20 occurrences, 155 keywords were extracted with a frequency of 17,493 occurrences (comprising 60% of total frequencies). It exceeded Bradford's law, and had the potentiality of showing major research content of iMetrics.

After the determination of the keyword co-occurrence rate, a square matrix comprising 155 frequently repeated keywords was formed, one in which the rates related to diagonal cells equated to zero. Using UCINET (Borgatti, Everett, & Freeman, 2002), the matrix was converted into a correlation matrix. Afterwards, hierarchical clustering was performed by SPSS. The multidimensional scaling map was prepared by using UCINET. Considering the aforementioned points and the importance of mapping a strategic diagram in co-word studies, a square matrix and a subsequent co-relation matrix were made for each cluster by regarding keywords included in it at the final step. The centrality and density of each matrix were measured and a strategic diagram was drawn.

4. Results

Table 2 lists 30 high-frequent keywords. The frequency ranks from the first to the fourth belonged to "Impact Indicators' (with 1430), "Citation Analysis" (with 1135), "Scientific Collaboration" (with 627) and "H-Index" (with 579), respectively. Fig. 1 shows the network structure of 155 highly frequent keywords.

After defining a threshold for including keywords in co-word analysis, the rate of keyword co-occurrence was measured. In this step, the rates of co-occurrence of 155 highly frequent keywords with all keywords included in the studied papers were measured. Table 3 indicates the frequency distribution of 30 highly frequent co-word pairs.

4.1. iMetrics viewed through the lenses of "Author keywords" vs. "Keywords plus"

As mentioned earlier, WoS records have two keyword categories: author keywords and Keywords Plus. An exploratory analysis of the two sets of keywords can be led to a better understanding of iMetrics research. This has been conducted for those records that have both types of keywords. Results indicated that of 5944 records, 2197 have both types of keywords. Table 4 shows the top 30 author keywords versus top 30 keywords Plus.

Based on two types of keywords appeared in Table 4 it seems that most of Keywords Plus are one-worded. A closer look reveals that author keywords have more concept-oriented than Keywords Plus; these words convey a deeper meaning to the readers of iMetric papers. The network structures of 155 highly frequent author keywords and Keywords Plus are shown in Figs. 2 and 3. After conducting co-occurrence analysis among author keywords, it was revealed that "Bibliometrics*Citation Analysis," "H-Index*G-Index," "Bibliometrics*Citations," are highly frequent co-word pairs. Moreover, findings showed that "H-Index*Impact," "Impact*Indicators," "Citations*Impact," are highly frequent co-word pairs within Keywords Plus, respectively.

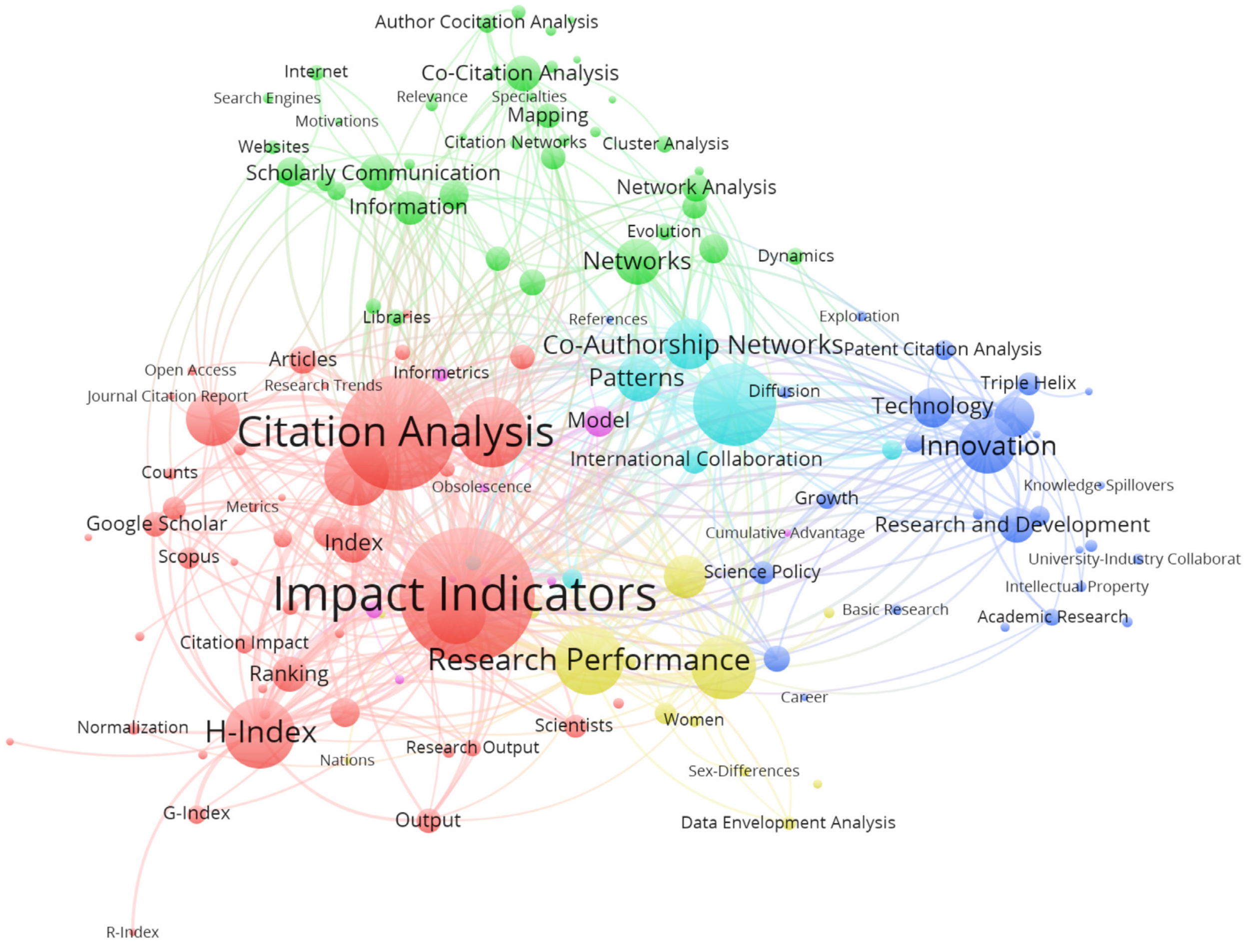

Fig. 1. The network structure of 155 high-frequent keywords.

Table 3
The frequency distribution of 30 top co-words.

Rank	Co-words	Frequency	Rank	Co-words	Frequency
1	Citation Analysis* Impact Indicators	529	16	Innovation*Patents	142
2	H-Index* Impact Indicators	368	17	Productivity* Scientific Collaboration	139
3	Impact Indicators* Research Performance	334	18	Impact Factor* Impact Indicators	134
4	Citation Analysis* H-Index	242	19	Patterns* Scientific Collaboration	129
5	Impact Indicators* Journals	236	20	Citation Analysis* Scientific Collaboration	124
6	Impact Indicators* Scientific Collaboration	228	21	Impact Indicators* Universities	119
7	Co-Authorship Networks* Scientific Collaboration	223	22	G-Index* H-Index	115
8	Citation Analysis* Journals	216	23	H-Index* Journals	111
9	Bibliometric Analysis* Citation Analysis	206	24	Innovation* Research and Development	107
10	Impact Indicators* Publication Analysis	200	25	Impact Indicators* Ranking	107
11	Impact Indicators* Productivity	199	26	Impact Indicators* Innovation	104
12	Citation Analysis* Impact Factor	189	27	Productivity* Research Performance	104
13	Citation Analysis* Publication Analysis	185	28	Citation Analysis* Productivity	103
14	Bibliometric Analysis* Impact Indicators	178	29	Citation Analysis*Index	102
15	Citation Analysis* Research Performance	144	30	Impact Indicators*Index	100

For a better depiction of the iMetrics structure, the results of hierarchical clustering, multidimensional scaling, and strategic diagram are reported below.

4.2. Hierarchical clustering

Among multivariate statistical methods, hierarchical clustering was performed at first: the correlation matrix provided by co-word frequency matrix was transmitted into SPSS, and the clusters and co-word dendrogram were prepared. Hierarchical clustering basically includes mapping clusters by employing Ward's method and Squared Euclidean Distance. Ward's method

Table 4
Top 30 author keywords vs. Keywords Plus.

No.	Author Keywords	Frequency	No.	Keywords Plus	Frequency
1	Bibliometrics	353	1	Impact	319
2	Citation Analysis	182	2	Indicators	270
3	H Index	179	3	Citations	231
4	Citations	124	4	H-Index	217
5	Scientometrics	72	5	Journals	193
6	Patents	68	6	Innovation	189
7	Research Evaluation	67	7	Publications	176
8	Impact Factor	59	8	Networks	167
9	Collaboration	58	9	Patterns	151
10	Social Network Analysis	49	10	Performance	150
11	Webometrics	47	11	Index	147
12	Co-Authorship	46	12	Technology	136
13	Innovation	46	13	Knowledge	122
14	Web Of Science	45	14	Productivity	108
15	Network Analysis	45	15	Universities	103
16	Research Collaboration	43	16	Citation Analysis	102
17	Bibliometric Indicators	41	17	Research-And-Development	100
18	Scientific Collaboration	38	18	Information	98
19	Universities	37	19	Collaboration	94
20	Research Performance	35	20	Research Performance	93
21	Journal Impact Factor	35	21	Model	85
22	Nanotechnology	34	22	Bibliometrics	83
23	G-Index	32	23	Output	77
24	Peer Review	29	24	Scientific Collaboration	74
25	Productivity	29	25	Quality	72
26	Citation Networks	28	26	Web	71
27	Research Productivity	26	27	Articles	66
28	Evaluation	26	28	Scientists	59
29	Information Retrieval	25	29	Information-Science	59
30	Text Mining	25	30	Communication	56

has been used in several co-word studies for hierarchical clustering analysis (e.g., Ding et al., 2001; Lee & Jeong, 2008; Liu et al., 2012; Neff & Corley, 2009; Zong et al., 2013). The dendrogram of hierarchical clustering is illustrated in Fig. 4. As the studied keywords were relatively high, the dendrogram was expanded into 2 pages. As the dendrogram indicates, the co-word analysis resulted in the formation of 11 subject clusters.

Table 5 shows the results of hierarchical clustering analysis, with keywords included in each cluster. It is worth mentioning that, in some clusters, keywords are observed that have no direct relationship with the subject of the cluster. This is common in co-word analyses: Hu et al. (2013) have studied such keywords with low co-word frequencies, along with correlation coefficients other than the main, highly frequent keywords.

Cluster 1. Scientometric databases and indicators. There are 16 keywords in this cluster, including “Google Scholar,” “Scopus,” “Web of Science,” “Impact Indicators,” “H-Index,” and “Quantitative Analysis.”

After the establishment of Institute for Scientific Information (later renamed Thomson Scientific), by Eugene Garfield and after other citation databases, they simplified the study of iMetrics so that work on very high data volume which was hardly carried out in the past, became possible and exploiting the capabilities of the database in turn helped in establishing new and more accurate indexes for the evaluation and efficacy of individuals and institutions. For this purpose, these citation databases and their indicators, became the subject of prospective researches themselves.

Cluster 2. Citation Analysis and Theoretical Foundations. As the biggest cluster, this cluster comprised 35 highly frequent keywords, some with very high frequencies. These keywords included, among others, “Citation Analysis,” “Citation Impact,” “Bibliometric Analysis,” “Journals,” “Impact Factor,” “Self-citation,” “Normalization,” and “Quality Assessment,” all of which are related to iMetrics. The structure of this cluster’s network is shown in Fig. 5. The placement of the keyword “Citation Analysis” in the center of the network, and its frequent co-occurrence with other keywords obviously demonstrates its importance in this cluster.

Citation analysis is one of the oldest and rooted fields of study in iMetrics and the number of "citations" is the basis for calculating several indicators of iMetrics.

Cluster 3. Sociology of Science. Nine keywords were included in this cluster, such as “Gender Differences,” “Women,” and “Higher Education”. Sociology of science is a field that in fact analyzes the interaction between science and society. In more general terms, the major areas of study of sociology of science include: the relationships of science with other social institutions, science and other aspects of culture, system of social relations in the realm of science, the social nature of scientific knowledge, social factors associated with the growth of science, social structure of scientific jobs, social organizations of science, and social stratification in science.

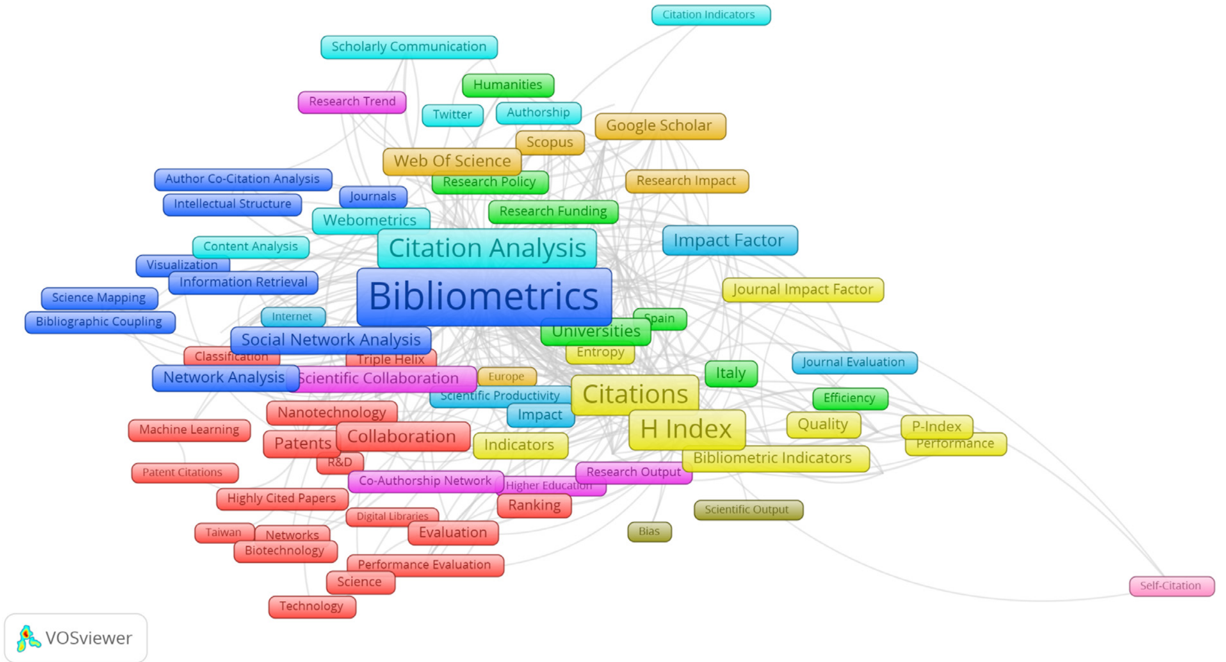

Fig. 2. The network structure of 155 high-frequent author keywords.

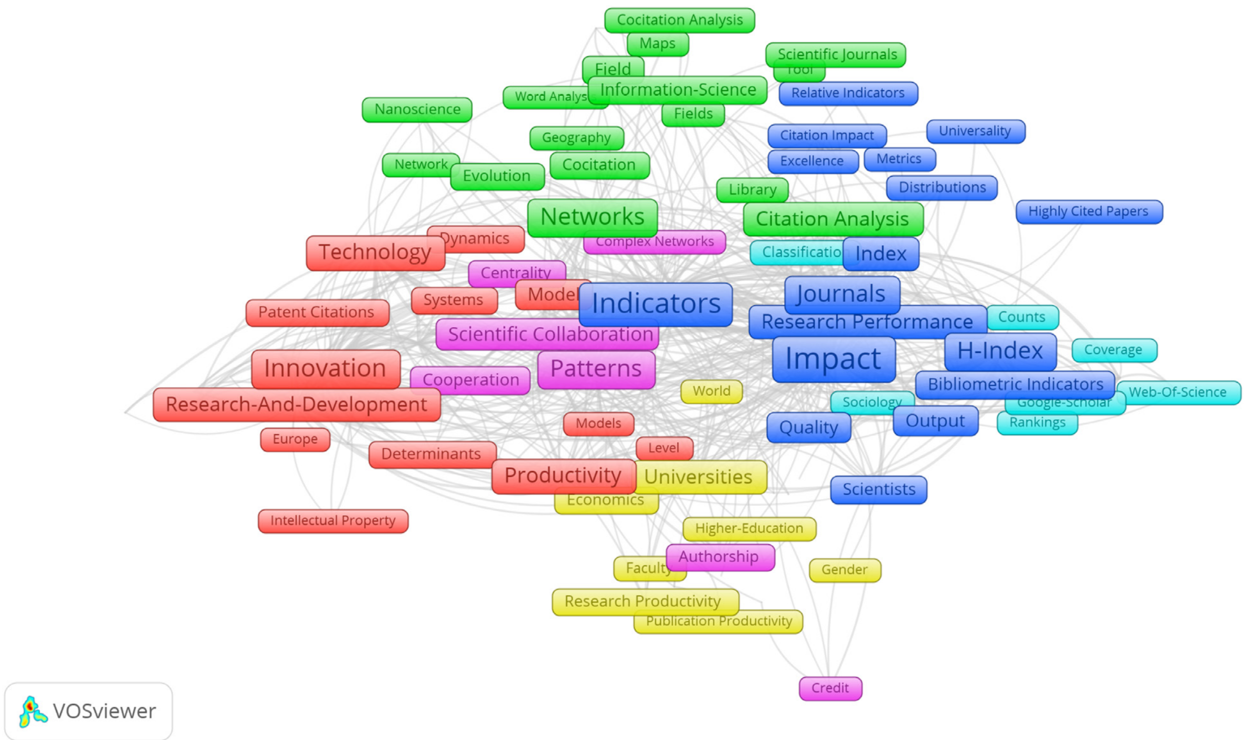

Fig. 3. The network structure of 155 high-frequent Keywords Plus.

Cluster 4. Issues Related to Ranking of Universities, Journals, etc. As one of the smaller clusters, this cluster comprised 8 keywords, such as “Journal Citation Report,” “Journal Ranking,” and “University Ranking”. Discussion of accreditation and reputation of the University and journals have always been of interest to researchers and therefore different ratings for the assessment of universities and journals are presented and discussed. Several researchers have scrutinized different universities and journals based on these rankings and the results of the co-occurrence analysis in this studies are well-illustrated in this study in the form of a cluster.

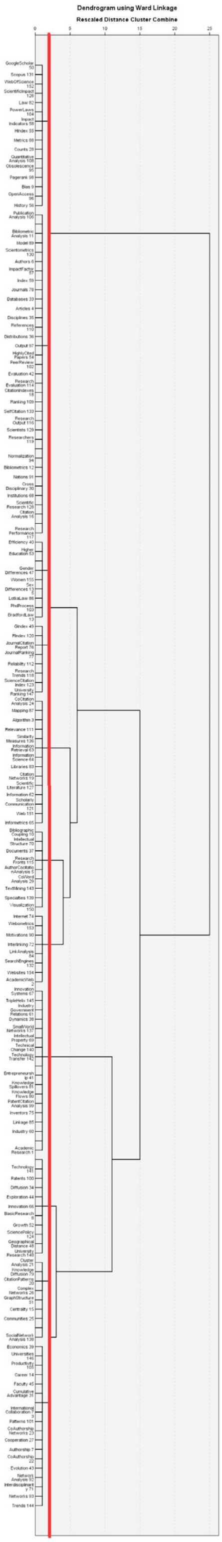

Fig. 4. Dendrogram from hierarchical clustering with co-word method.

Table 5
Information on co-word clusters based on the dendrogram diagram.

Cluster	No. of keywords	Cluster theme	Keywords in the cluster
1	16	Scientometric databases and indicators	Google Scholar; Scopus; Web of Science; Scientific Impact; Law; Power Law; Impact Indicators; H-Index; Metrics; Counts: Quantitative Analysis; Obsolescence; Page Rank; Bias; Open Access; History.
2	35	Citation analysis and theoretical foundations	Publication Analysis; Quality Assessment; Bibliometric Analysis; Model; Scientometrics; Authors; Impact Factor; Index; Journals; Databases; Articles; Disciplines; References; Distributions; Output; Highly Cited Papers; Peer Review; Evaluation; Research Evaluation; Citation Indexes; Ranking; Self Citation; Research Output; Scientists; Researchers; Field Normalization; Normalization; Bibliometrics; Nations; Cross Disciplinary; Institutions; Scientific Research; Citation Analysis; Citation Impact; Research Performance.
3	9	Sociology of science	Efficiency; Higher Education; Data Envelopment Analysis; Gender Differences; Women; Sex Differences; Lotka Law; Phd Process; Bradford Law.
4	8	Issues related to ranking of universities, journals, etc.	G-Index; R-Index; Journal Citation Report; Journal Ranking; Reliability; Research Trends; Science Citation Index; University Ranking;
5	14	Information visualization and retrieval	Co-Citation Analysis; Mapping; Algorithm; Relevance; Similarity Measures; Information Science; Information Retrieval; Libraries; Citation Networks; Scientific Literature; Information; Scholarly Communication; Web; Informetrics.
6	9	Mapping the intellectual structure of science	Bibliographic Coupling; Intellectual Structure; Documents; Research Fronts; Author Co-citation Analysis; Co-Word Analysis; Text Mining; Specialties; Visualization.
7	8	Webometrics	Internet; Webometrics; Motivations; Interlinking; Link Analysis; Search Engines; Websites; Academic Web.
8	18	Industry–university–government relations	Innovation Systems; Triple Helix; Industry Government Relations; Dynamics; Small World Networks; Intellectual Property; Technical Change; Technology Transfer; University-Industry Collaboration; Entrepreneurship; Knowledge Spillovers; Knowledge Flows; Patent Citation Analysis; Inventors; Linkage; Industry; Research and Development; Academic Research.
9	11	Technomettrics (innovation and patents)	Science And Technology; Technology; Patents; Diffusion; Exploration; Innovation; Basic Research; Growth; Science Policy; Geographical Distance; University Research.
10	9	Network analysis	Cluster Analysis; Knowledge Diffusion; Citation Patterns; Complex Networks; Graph Structure; Centrality; Communities; Social Network Analysis.
11	18	Scientific collaboration in universities	Economics; Universities; Productivity; Career; Faculty; Cumulative Advantage; Scientific Collaboration; International Collaboration; Pattern; Co-Authorship Networks; Co-Authorship; Cooperation; Authorship; Evolution; Network Analysis; Interdisciplinarity; Networks; Trend.

Cluster 5. Information Visualization and Retrieval. Comprising 14 keywords, the cluster included keywords, such as “Mapping,” “Algorithm,” “Similarity Measures,” and “Information Retrieval.” One of the first objectives of iMetrics studies is actually to help in retrieving and visualizing information, and in the meantime different researchers have provided algorithms, software, and theories including mapping based on their studies and these concepts are well-demonstrated on keywords of cluster 5.

Cluster 6. Mapping the Intellectual Structure of Science. This cluster comprised 9 keywords closely associated to one of the traditional subjects of iMetrics - “mapping the structure of knowledge.” “Bibliographic Coupling,” “Intellectual Structure,” “Co-word Analysis,” and “Author Co-citation Analysis” are some of these keywords. The development of Science in different areas is indebted to the effort of previous scientists. Researchers in a scientific area usually assess the works of previous scientists in order to identify the boundaries of knowledge in their specific area; in other words, researchers depend on the previous science, to continue with the future science of their field. Amongst the most important techniques that can be used to study the structure of knowledge «co-word analysis», «author co-citaiton analysis», and «bibliographic coupling» could be stated that today are frequently observed in iMetrics studies.

Cluster 7. Webometrics. With 8 keywords, such as “Link Analysis,” “Interlinking,” and “Websites,” this relatively small cluster deals with webometrics. Webometrics is studying the quantitative aspects of the creation and use of Web information resources, structures and technologies related to bibliometric and informetrics approaches (Björneborn, & Ingwersen, 2001). Webometrics, which was first presented by Almind and Ingwersen (1997) majorly deals with the analysis of web pages and analysis of the structure of web links.

Cluster 8. Industry–University–Government Relations. As the second largest cluster of co-word analysis, this cluster included 18 highly frequent keywords. Its broad subject is one of the major iMetrics subjects in various countries. It comprised keywords, such as “Triple Herix,” “Industry–Government Relations,” “Industry–University Co-operation,” “Flow of Science,” and “Entrepreneurship.”

One of the concerns of science policy makers has always been that the scientific findings be applied in the service of humanity and in this regard, universities, and research centers have been trying to present their scientific findings to

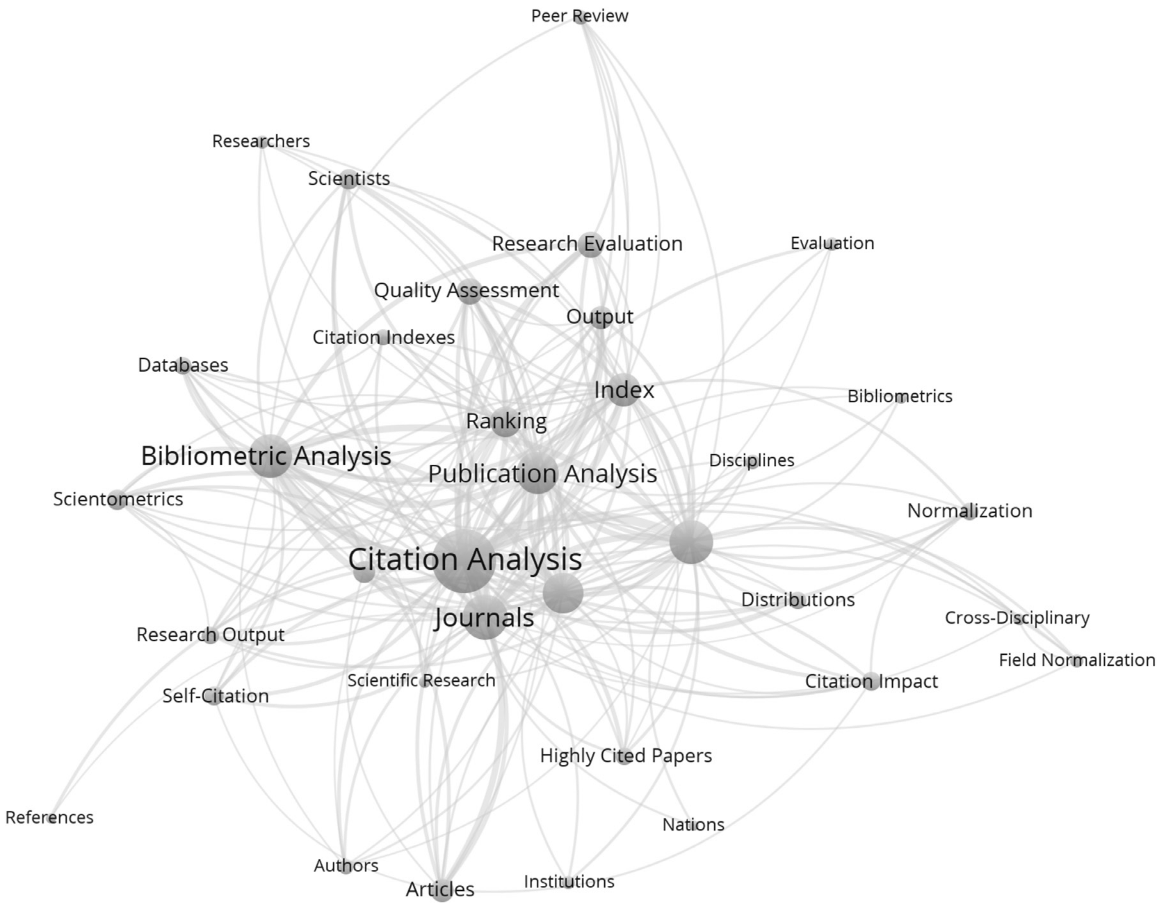

Fig. 5. The network structure of keywords in cluster 2, based on density view.

industry so as to produce technology and product. The relationship between industry and academia generally deals with the associated discussions related to this process. This very important and complex process required assessment and review and one of the most important methods that can rightly perform this task is iMetrics studies and this task is well noticeable in the keywords applied in the cluster 8.

Cluster 9. Technometrics (Innovation and Patents). This cluster comprised 8 highly frequent keywords including, among others, "Patents," "Technology," and "Innovation". This demonstrated one of the sub-field in iMetrics referred to as "technometrics." One attractive aspect of iMetrics studies is the examination of patents in diverse scientific fields using bibliometric indicators. Technometrics is closely related to iMetrics and with analyzing statistics and indicators of patents offers an important tool for determining process of practical researches.

Cluster 10. The Basics of Network Analysis. Consisting of 9 highly frequent keywords, such as "Social Network Analysis," "Graph Structure," "Complex Networks," and "Centrality," this cluster has gained extensive application in iMetrics. A network is a set of segments (players) and relationships (nodes) that takes place among them. The concept of network emphasizes that each vertex has links with other vertices, and each of them in turn is linked to a number of other vertices. Thus the network structure can be defined as patterns or rules in relations between those segments that establish interaction. Hence, scientific networks and social networks analysis is one of the interesting and complicated issues in the study of iMetrics that is discussed with techniques and methods based on mathematical principles and theories of sociology and indicators in this area.

Cluster 11. Scientific Collaboration in Universities. With 18 highly frequent keywords, such as "Scientific Collaboration," "International Collaboration," and "Co-Authorship," this cluster was one of the significant clusters. Scientific collaboration is one of the noticeable outcomes of collaboration among authors and it is a complex phenomenon that is the outcome of sharing their capabilities, which enhances the production of new science. Scientific collaboration is created with increasing knowledge complexity and as a result of increased demand for more specialization and interdisciplinary skills in research, science policy makers pay special attention to the issue of national and international collaboration among researchers in academic institutions, which is usually presented in the form of co-authorship.

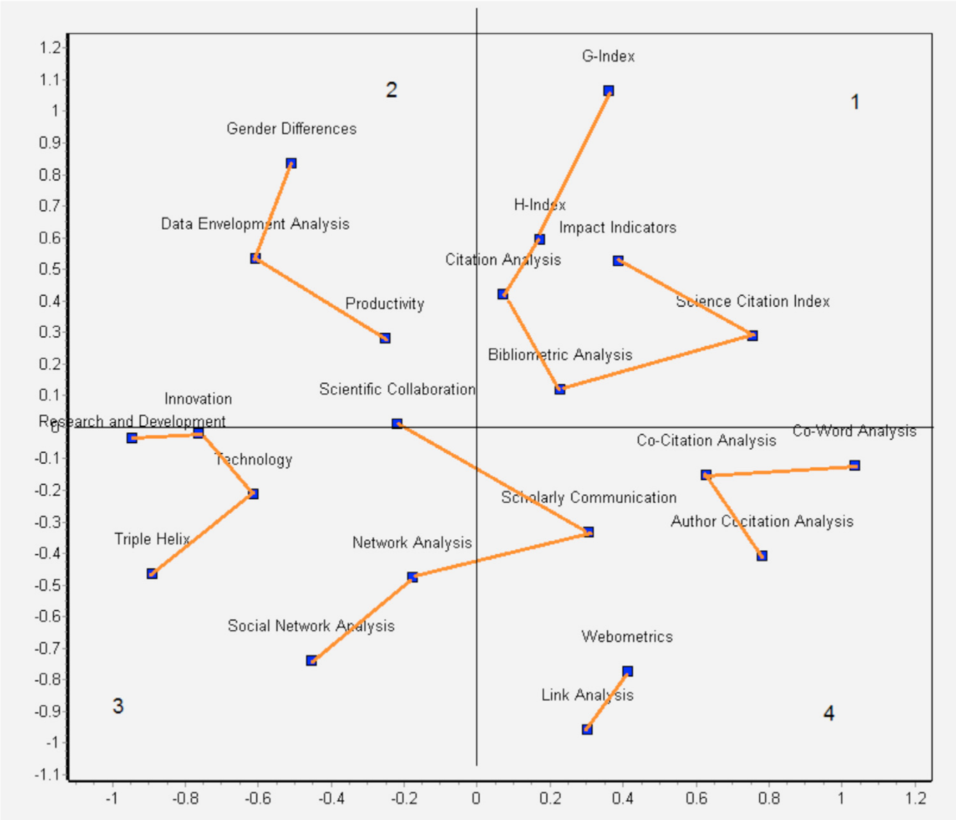

Fig. 6. Two-dimensional map from co-word analysis of iMetrics subjects.

4.3. Multidimensional scaling

The multidimensional scaling method was employed in order to have a deeper understanding of iMetrics subject structure. The two most highly frequent co-word keywords from each of the clusters were chosen as representatives. Afterwards, a 22-folded square matrix was drawn, and a correlation matrix was formed by applying the UCINET software. The related file was recalled in the software, and a two-dimensional map was drawn from iMetrics subjects. Initial analysis concerning the scree plot revealed that the largest perfection in terms of stress occurs when shifting from one to two dimensions. Thus as in several co-word analysis studies (including, Hu et al., 2013; Liu et al., 2012; Ravikumar et al., 2015), a two-dimensional solution was chosen. In this study, the amount of stress value and RSQ for the two-dimensional solution equals to 0.115 and 0.942, respectively (Fig. 6).

The multidimensional scaling method resulted in merging of some keywords, based on their placement and distance from each other and the formation of 6 general clusters out of 11 primary clusters. The horizontal axis (first dimension) in the two-dimensional matrix demonstrates the extent of inter-correlation among the subject clusters, whereas the vertical one (second dimension) demonstrates the focus of the clusters. Considering the map in Fig. 6, it is evident that the clusters extracted from multidimensional scaling are close to one another, except for the Webometrics cluster.

As observed in Fig. 6, the four clusters of “webometrics,” “scientific collaboration,” “co-citation analysis,” and “technometrics” were placed in the lower part of the figure, while “sociology of science” and “citation analysis and theoretical foundations” were placed in the upper part of the diagram. Therefore, the focus of iMerics as a field of study has been from the four lower clusters towards the two upper clusters. The clusters have been distributed in each part of the diagram, its second part containing the lowest keyword density than the three others.

4.4. Strategic diagram

In this section, a strategic diagram was drawn based on the network’s centrality and density. A strategic diagram is mostly used to describe the internal relations within a cluster, as well as the interactions among different fields. Strategic diagram considers both centrality and density, and thus can also describe the dynamics of research themes (Hu & Zhang, 2015). Initially, a frequency matrix and the subsequent correlation matrix were formulated for each of the eleven clusters. Afterwards, using UCINET software, the centrality and density of each cluster and the mean value of centralities and den-

Table 6
The centrality and density of clusters from co-word analysis.

Cluster	Centrality	Density
1. Scientometric databases and indicators	533.45	0.38
2. Citation analysis and theoretical foundations	17,087.03	0.65
3. Sociology of science	26.71	0.20
4. Issues relatod to ranking of universities, journals, etc.	7.26	0.11
5. Information visualization and retrieval	1144.56	0.69
6. Mapping intellectual structure	216.53	0.61
7. Webometrics	173.84	0.67
8. Industry–University–Government collaboration	1434.93	0.52
9. Technomettrics (innovation and patents)	566.60	0.72
10. Network analysis	67.80	0.41
11. Scientific collaboration in universities	2428.95	0.68

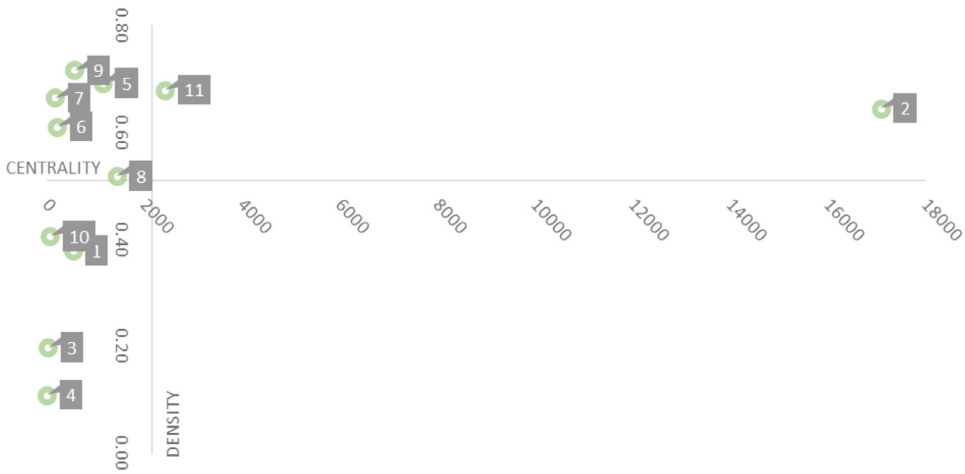

Fig. 7. The strategic diagram of eleven clusters.

sities were measured. According to centrality and density data of each cluster (Table 6), a strategic diagram was drawn to clarify the maturity and cohesion of each cluster (Fig. 7).

As indicated in Table 6, clusters two (Citation analysis and theoretical foundations), eleven (Scientific collaboration in universities), eight (Industry–University–Government collaboration), and five (Information visualization and retrieval) have a higher centricity. This implies that the mentioned clusters have connected very well with other clusters, and topics in them are at the center of discussion of iMetrics. In addition, clusters four (Issues related to ranking of universities, journals), three (Sociology of science), and ten (Network analysis) that have a lower centricity suggests that these clusters are counted as marginal clusters of iMetrics.

Conversely, clusters nine (Technometrics), five (Information visualization and retrieval), and eleven (Scientific collaboration in universities) have a higher density compared to other clusters. This implies that these clusters are of high internal associations and topics contained in them are well-developed and have attained good maturity. Furthermore, clusters four (Issues related to ranking of universities, journals), three (Sociology of science), one (Scientometric databases & indicators), and ten (Network analysis) which had a low density suggests that these clusters have remained underdeveloped.

The strategic diagram of the clusters drawn from co-word analysis in iMetrics is shown in Fig. 7. The origin of the diagram was set on points 2153.36 and 0.51, based on the mean value of centrality and the mean value of density, respectively. The horizontal axis in the strategic diagram indicates centrality and the interactive power of each studied cluster. The higher the centrality of a cluster, the more important it is. The vertical axis shows density and internal relations in a research field. The greater the density of a cluster, the higher is its potentiality for development and maintenance (Liu et al., 2012).

An interesting finding regarding the distribution of clusters in the strategic diagram is that no cluster was placed in part 4 of the diagram. In general, the clusters positioned in part 4 of the strategic diagram are axial, but underdeveloped. There is no such cluster in iMetric.

As Fig. 7 illustrates, the two clusters (Cluster 2: Citation Analysis and Theoretical Foundations, and Cluster 11: Scientific Collaboration in Universities) were located in part 1 of the strategic diagram. This suggests that these clusters occupy the axis and center of the iMetrics co-word network. These subject clusters are well developed, and have powerful internal correlation and maturation. In other words, the high centrality of these clusters (placement in the centre of the research network) indicates that these clusters have a central place in the general iMetrics network, and stand in an expanded and powerful relation with other clusters. Conversely, the five clusters (Cluster 5: Information Visualization and Retrieval, Cluster

6: Mapping Intellectual Structure of Science, Cluster 7: Webometrics, Cluster 8: Industry–University–Government Relations, and Cluster 9: Technometrics) were positioned in part 2 of the strategic diagram. This suggests that these clusters are not axial, but are developing. Besides, 4 clusters (including Cluster 1: Scientometric Databases and Indicators, Cluster 3: Sociology of Science, Cluster 4: Issues related to Ranking of Universities, Journals, etc., and Cluster 10: Basics of Network Analysis) are positioned in part 3 of the strategic diagram. These clusters had low centrality and density levels; they have a relatively discontinuous structure, are underdeveloped and immature, and are in the margins of the iMetrics network.

5. Discussion and conclusions

Through co-word analysis one can quantitatively recognize the knowledge domain of a certain research field, and explain the existing relations among its subjects. In this study, co-word analysis was used to explore subject clusters in iMetrics. For the sake of comprehensiveness, and as suggested by Zhang et al. (2016), we included both the Web of Science keyword categories. Primary findings revealed that keywords such as “Impact Indicators,” “Citation Analysis,” “Scientific Collaboration,” and “H-Index” had higher frequencies. Of course, this part of the research is basically different with the findings of Sedighi (2016), so that in the mentioned research, the most informetrics terms were keywords such as “communication”, “information systems”, “information technology”, “e-learning”, and “information science” respectively. It appears that just the use of network analysis methods available in software «Vosviewer» and «NodeXL», and not employing conventional methods such as designing correlation and square matrices and also not using hierarchical clustering methods have resulted in different changes in the study by Sedighi (2016).

Application of hierarchical clustering analysis led to the formation of 11 main subject clusters. The greatest cluster was “Citation Analysis and Theoretical Foundations,” making up 35 high-frequent keywords. Although hierarchical clustering can demonstrate clusters in a field of study, it has some limitations. For example, it hardly shows within-cluster interactions, or internal relations that would determine which cluster has centrality or is matured. The interpretation of clusters depends greatly on subjective factors, with the analysis of clusters requiring expertise in the field (Yang, Wu, & Cui, 2012). As a result, the strategic diagram is employed to complement hierarchical clustering in co-word analysis. Analysis of the strategic diagram showed that themes “Citation Analysis and Theoretical Foundations”, and “Scientific Collaboration in Universities” are two most comprehensive subject areas in iMetrics, and that they are more developed than other related subjects in the field. These clusters have established relations with other neighboring clusters. This is the case with the “Citation Analysis and Theoretical Foundations” cluster that has highest centrality as well as relatively high density. In general, and according to the results of part 1 of the strategic diagram, it can be mentioned that the core of iMetrics research focuses on clusters 2 (Citation Analysis and Theoretical Foundations), and cluster 11 (Scientific Collaboration in Universities). These clusters that do not have appropriate density and internal centricity not only have good stability but they also connect well with other clusters and they are in the center of iMetrics.

However, subjects such as “Scientometric Databases and Indicators”, “Sociology of Science,” “Issues Related to Rankings of Universities, Journals, etc.”, and “Basics of Network Analysis” have not matured or attained centrality yet. Concerning the placement of these themes in the strategic diagram, it can be claimed that these themes did not show established internal and external relations in the field and remained underdeveloped. Moreover, based on the high density of themes such as “Information Visualization and Retrieval”, “Mapping Intellectual Structure of Science”, “Webometrics”, “Industry–University–Government Relations”, and “Technometrics”, it can be mentioned that they have powerful internal relations and a suitable level of maturation.

In spite of their similarity with those of Courtial (1994), the clusters extracted from the co-word analysis in this study were different in several aspects. For instance, “databases,” “citation analysis,” “scientific assessment,” “law of scatter,” “journal impact factor,” and “author productivity” were of clusters extracted by Courtial (1994). One of the major reasons for such differences is that about two decades has elapsed since Courtial’s study, with new subjects having emerged in the field. This study was a reflection of such changes. Furthermore, a part of the results of this study are in agreement with the results of Ravikumar et al. (2015). Similar with the results of Ravikumar et al. (2015), this study indicated that topics such as international collaboration, Webometrics, link analysis, and web sites compared to other iMetrics discussions are of stronger status and topics such as citation index, Lotka Law, University Ranking are not a good status in terms of internal stability and external relations. On the contrary, unlike the results by Ravikumar et al. (2015), the findings of this study indicate that issues such as co-citation analysis, and co-authorship network are in a better status compared to cluster analysis discussions and citation patterns. Of course one of the reasons for such different results can be short period of time as well as low number of records in the research of Ravikumar et al. (2015).

Given that the field of iMetrics has achieved its specific cognitive framework and in a way it has separated itself from the area of Information Science, it is anticipated that the current study be able to help identify discussions relating to this field. However, some items may have limited the findings of this research. For instance, though at most studies of iMetrics, records of Web of Science (WoS) are used, yet journals that are presented in WoS are naturally international, but its emphasis is more on English journals; this is why, some iMetrics studies are conducted non-English and are not indexed in WoS. In addition, some foundations and studies of iMetrics are published in form of book which are not dealt with in this study due to the absence of information of books in WoS. In spite of this, with the use of exploited search strategy in this study, it has tried to provide studied records with adequate comprehensiveness so as to be able to reveal iMetrics status with co-word analysis. That is why it is suggested that in a follow-up study, the structure of iMetrics research be conducted in the non-English-speaking world. In addition, since in this study both types of keywords (author keywords and Keywords Plus) are included in the analysis as combined, it is suggested to deal with examination and comparison of iMetrics' structure with two types of author keywords and Keywords Plus, individually. Also, it is presented to use the words of the entire text in order to use co-word analysis and to compare the results with the results of the present research.

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