DSI DATA SCIENCE AND INFORMETRICS
VOL.3, NO.1, FEB. 2023

RESEARCH ARTICLE

# Research on potential influential scholars in the field of information science and their cooperative characteristics

Jianhua Hou, Xiucai Yang, Haiyue Yao, Yang Zhang*

School of Information Management, Sun Yat-Sun University, Guangzhou, China

**ABSTRACT**

With the continuous development of social media, the ways and means of academic influence evaluation of scholars are increasing rapidly. The emergence of the Citation Network Structural Variation model method breaks the traditional way of identifying the influence of scholars through scientometrics index, author cooperation or node indicators in author citation network structure. Based on this method, CiteSpace software tool is used to detect scholars with potential influence in the field of Information Science and reveal the cooperative characteristics of scholars with potential influence. The study found that the most potentially influential five-pointed star scholars in the field of Information Science mainly include Leydesdorff L, Bornmann L, Thelwall M, Bar-Ilan J, Waltman L, Huang MH, Rousseau R and others. Pentagram scholars are usually located at the core of different cooperative groups in the author's cooperative network. Other influential non-pentagram scholars and pentagram scholars maintain a high frequency of cooperation and have a high similarity in research direction.

**KEYWORDS**

Scholars' potential influence; Citation Network Structural Variation model; Author collaboration; CiteSpace

## 1 Introduction

The academic influence analysis of researchers has always been an important issue in the fields of Information Science and Scientometrics. The evaluation of a researcher's academic influence mainly includes two research perspectives: one is through scientometric indicators, such as productivity, collaborations performance, citation counts, H-index and other quantitative indicators for direct display (Liu, 2018; Du et al., 2014; Ma et al., 2017; Kumar, 2021). The second aspect is to analyze the academic influence of researchers through author cooperation or node indicators in the author citation network structure (network centrality, Burst, etc.) (Li & Li, 2018; Huang & Liu, 2013). In Information Science, many studies have analyzed academic influence from citation network analysis through node indicators of a citation network. This aspect of research can be traced back to 1981 (White et al., 1981). Through the A-

* Corresponding Author: zhyang2@mail.sysu.edu.cn

CA method, it revealed the knowledge structure of 39 scholars in the field of Information Science. Subsequent researchers also use ACA or co-author methods to analyze researchers in Information Science, and identify researchers with academic influence through scientometric indicators. However, at present, with the emergence of a large number of new academic social media, the evaluation methods and approaches to the academic influence of researchers are also rapidly increasing. With the rapid growth in the volume of research papers in the field of Information Science, new researchers are joining the field, resulting in the emergence of new knowledge and cutting-edge topics. A large number of researchers are emerging, so it is important to identify potential researchers, who will make an important contribution to the knowledge. The influence of the introduction of new knowledge on the knowledge structure of the existing research field is an important aspect in judging the development of scientific activities. In 2012, Chen (2012) proposed a "Structural Variation model", which differs from the traditional citation network-based analysis in that it analyses the potential influence of the introduced paper from the perspective of the cited paper and the impact of the newly introduced paper on the structure of the underlying citation network. This provides a new perspective on the potential influence of scholarship.

From the perspective of the transformation of the existing knowledge base network structure caused by the introduction of papers of author(s), this study explores the potentially academic influence of scholars in the field of Information Science and the cooperation characteristics of these potentially influential scholars (Refers to scholars who have not yet revealed but will show high influence in the future or scholars who are showing high academic influence) through the influence of cited papers on the structure of the co-cited basic knowledge network. This article mainly answers the following questions:

(1) Through the Citation Network Structural Variation model, who are the scholars with the most potentially academic influence in the field of Information Science?

(2) What are the cooperative characteristics of potentially academic influencers revealed through TF*IDF algorithm and Pennant Diagram?

The main contributions of this study are: On the one hand, compared with traditional studies that identify and judge the academic influence of scholars through scientometric indicators such as productivity, the number of collaborations, citation counts, and the node indicators in the citation network structure of authors, we emphasize identifying the potentially academic influence of scholars from the impact of the introduction of new knowledge on the knowledge structure of existing research fields. This provides important supports for academic talent mining, introduction, and evaluation in related institutions. On the other hand, we reveal the general cooperation characteristics of potentially influential scholars, which provides an important basis for choosing the path of how scholars located in different positions in the network can quickly improve their academic influence.

## 2 Literature Review

In scientometrics research, the study of academic influence of scholars has always been a hot issue for researchers. There are many studies on the academic influence of scholars in different fields from different perspectives. On the whole, the relevant studies mainly include the following aspects:

On the one hand, the influence of researchers or papers can be revealed through scientometric indicators. At present, the influence of researchers or papers is mainly measured by citation counts, such as total citations, H-index, and the number of citations per paper

(Hirsch, 2005; Egghe & Rousseau, 2006; Jin et al., 2007; Moed, 2011). Ajiferuke et al. (2010) conducted an initial investigation of the concept of citer analysis, where the number of citers is the basis for research impact assessment, rather than the number of citations, and found a strong positive relationship between citations and citer-based measures relationship. In recent years, there has been a growing body of research on influence through Altmetrics, including new analytical software. Bornmann (2014) analyzed the advantages and disadvantages of Altmetrics for assessing influence. The influence of researchers or papers is greatly expanded through social media platforms (Erdt et al., 2016; Thelwall & Kousha, 2015; Kousha & Thelwall, 2015), and the broader non-academic influence is assessed through a wider range of resources, including social media posts, press releases, news articles and comments generated by academic works (Ravenscroft et al., 2017).

On the other hand, research on researchers' academic influence through citation network analysis or author collaboration network analysis has received increasing attention. For example, the citation network index is used to measure the influence of researchers in the cooperation network. Micro-network metrics such as scholar centrality, closeness centrality, and betweenness centrality are used to measure the influence of researchers in collaborative networks (Yan & Ding, 2009). Some analyses predict the future influence of a document or a researcher through the citation network's structural information. There are also beginnings to use the citation network information provided at the time of publication to predict the future impact of a paper (Sebastian et al., 2017; Ajiferuke & Famoye, 2015). In 2012, Chaomei Chen (2012) proposed a theoretical and computational model that predicted the potential of scientific publications regarding the extent to which they changed the structure of existing virtual knowledge networks. This model is called the Citation Network Structural Variation model (SVA), which mainly focuses on the novel boundary-crossing connection of the knowledge space introduced by the new document, and predicts the future potential influence of the newly introduced document through the boundary-crossing effect. Using this Citation Network Structural Variation model, Chen (2017) analyzed the underlying structural variation of the paper in the field of Information Science.

In addition, there is also an analysis of the academic influence of researchers through the impact of author collaboration on output performance. In the field of academic research, methods established by research centers or networks, typically through collaborative relationships, will actively influence the performance of researchers by enabling the exchange of existing resources, knowledge, and experience (Galvez & Shrum, 2011). More and more researchers are applying the SNA approach of collaborative networks to detect academic influence (Liu et al., 2005; Rodriguez & Pepe, 2008; Newman, 2001; Newman et al., 2001). Most studies found a positive relationship between cooperation and productivity (Corley & Sabharwal, 2010). In some cases, however, cooperation can even have a negative impact on productivity (Franceschet & Costantini, 2010). Contandriopoulos et al. (2016) argued that there was a strong link between researchers' structural positions in collaborative networks and their scientific performance. Ronda-Pupo et al. (2016a, 2016b) took the management field in Latin America as an example, and analyzed the impact of researcher collaboration on research output. In general, scientific collaboration can improve the performance of research output. However, it also depends on the model of collaboration, the motivation for collaboration, and the position of researchers in the collaborative network. Revealing the influence of author cooperation on researcher output through author cooperation network analysis, or revealing the academic influence of researchers through author citation analysis are currently important methods for analyzing scholars' influence, and some studies combine the two for analysis. Generally, there is a positive correlation between author collaboration or author citation and author academic influence (Yan & Ding, 2009).

Existing studies mainly analyze the academic influence of researchers through the number of citations or the index of citation (cooperation) network, but little research on the academic influence of the newly introduced literature (author) from the perspective of its influence on its knowledge infrastructure (citation network structure). This study uses SVA to analyze the academic influence of researchers in the field of Information Science. This paper introduces the author's perspective on the transformation of basic citation network structure, probes the potentially academic influence of researchers in Information Science, and analyzes the cooperation characteristics of potential influential scholars.

# 3 Data and Methods

This study mainly uses author collaboration analysis, author co-citation analysis and Citation Network Structural Variation model to identify the potential influence of scholars in the field of Information Science, and reveals the cooperation characteristics of potential influence scholars. We used the new version of CiteSpace visualization software system tools for auxiliary analysis (5.0.R3 SE) (Chen, 2017).

## 3.1 Data Collection

In the existing quantitative analysis of the knowledge structure of Information Science, most of the research objects choose 12 core journals as the literature data sources to define and analyze the knowledge structure of information science (Zhao & Strotmann, 2014). However, such analysis data selection has certain deficiencies. **First,** the selection of 12 journals was based on the article of White and McCain (1998). And they used the impact factors of the "Information Science & Library Science" classification in the Journal Citation Report of SSCI in 1993 as a reference. 12 journals were selected to define the field of Information Science. Subsequent studies in 12 journals were also determined according to this criterion. However, Information Science is a rapidly developing research field. Over the past 20 years, the current journals in this field and the impact factors of different journals have undergone significant changes. For example, Journal of Informetrics, founded in 2007 (renamed QSS in 2019.1), has developed rapidly in recent years. It's very influential in the field of Information Science. It is not reasonable to still select 12 journals to define Information Science. **Second**, although the JCR discipline classification system is reasonable and scientific, and high-impact factor journals have high influence and representativeness in disciplines, Information Science & Library Science is a multidisciplinary field including Information System, Information Science and Library Science. Even if the impact factors of the "Information Science & Library Science" classification in the current JCR or the 5-year average impact factors are selected as the selection criteria (Yang & Wang, 2015), they are selected according to the order of the impact factors. The selected journals can not fully represent the field of Information Science (most of the journals with large influence factors are information system journals). **Third**, even if the current impact factor is used as the selection criteria, and the journals "specially" belonging to Information Science are selected simultaneously, such selection criteria are highly subjective. At the same time, in terms of quantity, there is no clear standard for choosing how many journals to define the field of Information Science research, and there is also much subjectivity.

Therefore, we tried to select journals from another angle in this study. In order to select the core journals that can represent the high impact of the information science field in recent years, this study is based on JASIST, Scientometrics, and Journal of Informetrics (Staša & Leydesdorff, 2013). Extracting the largest journal Cluster representing Information Science in journal co-citation clusters by journal co-citation method. The threshold value was chosen as Top N=200 and log-likelihood ratio (LLR) clustering was chosen for clustering. After removing comprehensive and non-information science journals (such as Science, Nature, etc.), ten journals were finally identified as the data sources for this study (Table 1, Figure 1).

Using the retrieved data, we can examine the evolution of two types of networks — citation network and author co-citation network, and conduct an in-depth analysis of the changes in the structure of these networks, which helps predict the potential influence of scholars.

**Table 1** Data source journals and related data in the field of Information Science

| Journal | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|
| ARIST | 13 | 12 | 0 | 0 | 0 | 0 | 0 |
| Journal of Informetrics | 69 | 67 | 78 | 103 | 90 | 84 | 104 |
| Information Processing & Management | 60 | 68 | 82 | 92 | 52 | 68 | 75 |
| Journal of Documentation | 59 | 68 | 55 | 55 | 62 | 70 | 60 |
| Journal of Information Science | 50 | 52 | 43 | 62 | 66 | 59 | 59 |
| JANIS/JASIST | 243 | 212 | 215 | 220 | 215 | 216 | 230 |
| Library &Information Science Research | 45 | 46 | 41 | 45 | 31 | 47 | 33 |
| Research Evaluation | 35 | 42 | 37 | 32 | 30 | 37 | 32 |
| Information Research an International Electronic Journal | 93 | 82 | 87 | 130 | 103 | 94 | 47 |
| Scientometrics | 233 | 226 | 267 | 262 | 362 | 365 | 379 |

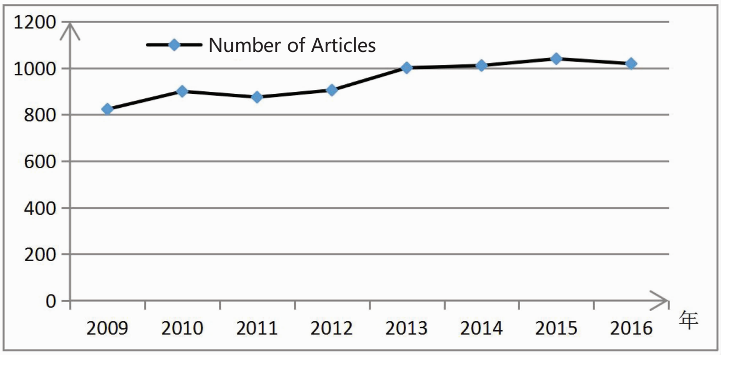



**Figure 1** Changes in the overall number of articles in 10 journals over time

## 3.2 Citation structure transformation model

The Citation Network Structural Variation model was proposed by Chaomei Chen in 2012, and it is a method for predicting potential changes in knowledge structure in knowledge or subject areas. The theoretical underpinnings of structural transformations are part of the theory of scientific discovery and can be explained in terms of boundary crossing, linkage, and synthesis mechanisms in the knowledge space (Chen, 2009). Among them, the boundary-spanning mechanism is also the core point of the SVA. Based on the existing citation network structure of the knowledge domain and its topic-based segmentation characteristics, the construction of the SVA is a method to represent the potential triggering structure transformation of the knowledge domain through the change degree of citation network structure caused by the introduction of a new scientific document. If an article introduces new links across different subject boundaries, we expect this can use the knowledge structure for a new turn. The basic assumption of the SVA is the degree of deviation from the current knowledge structure, and it is a necessary condition for the potential concept change in science (Chen, 2012). The SVA is composed of three indexes, that is, the rate of modularity change, the rate of linkage change among clusters, and the centrality dispersion. The first two measures are mainly based on the segmentation of the underlying network, but the third is not. Network segmentation refers to the segmentation of the network into non-overlapping node groups, such as the segmentation of citation network structure by a spectral clustering algorithm.

# 4 Results

## 4.1 Identification of scholars with potentially academic influence

Cluster analysis helps us understand the main topics related to Information Science. We now turn our attention to the trajectories of several major contributors in the field of these clusters. We measure the structural transformation of the knowledge base network through three metrics, namely (modularity) and modularity change rate (△M), inter-cluster linkage change rate (△CLw), and centrality divergence (△Ckl). The potential influence of scholars is studied from the perspective of newly introduced citing scholars leading to the transformation of the knowledge base network structure.

**The author´s △M analysis**

We used CiteSpace software to analyze the co-citation of the literature data from 2009 to 2016, and calculated the △M value of different scholars through the modularity value based on SVA. The top 30 researchers with the greatest impact on the degree of structural segmentation were listed in Table 2. Among them, Franceschini F and Leydesdorff L had the highest modularity change rate, which was 26.78 and 26.69, respectively. The modularity change rate of Zitt M, Egghe L, Bornmann L, Persson O were greater than 20. Compared with other scholars, the introduction of these scholars has led to an increase in basic knowledge network connections, making the segmentation of basic knowledge network structures clear, and further clarifying the boundaries between different informal academic groups.

**Table 2** Information of the top 30 authors with the largest △M

| Author | △M | Author | △M | Author | △M |
|---|---|---|---|---|---|
| Franceschini F | 26.78 | ThelWall M | 16.12 | Larsen PO | 10.99 |
| Leydesdorff L | 26.69 | Norris M | 15.91 | Vieira PC | 9.95 |
| Zitt M | 21.86 | Wang GB | 15.85 | Furner J | 9.55 |
| Egghe L | 21.78 | Perc M | 14.16 | Franzoni C | 9.47 |
| Bornmann L | 21.38 | Bar–ilan J | 14.06 | Yoon B | 9.44 |

| Author | △M | Author | △M | Author | △M |
|---|---|---|---|---|---|
| Persson O | 21.02 | Gomez–Sancho JM | 13.42 | Yu G | 9.34 |
| Kurtz MJ | 19.63 | Lancho–Barrantes BS | 13.12 | Yan EJ | 9.2 |
| Upham SP | 18.46 | Abramo G | 12.75 | Brown C | 8.7 |
| Davenport E | 16.9 | Huvila I | 12.49 | Mode HF | 8.69 |
| Franceschet M | 16.27 | Rafols I | 11.44 | Nederhof AJ | 8.69 |

**The author´s △CLw analysis**

We used CiteSpace to analyze the co-citations of the authors on the paper's data from 2009 to 2016, and calculated the $\triangle CL_w$ values of different scholars through the index of inter-cluster link change rate in the SVA. The top 30 researchers with the largest span of author citation links between different clusters were listed in Table 3. Among them, the model change rate of Leydesdorff L was the highest one, and the $\triangle CL_w$ value was 1.72, followed by scholars such as Abramo G, Thelwall M, Zitt M, Yan EJ, Zhang L, Bornmann L, whose $\triangle CL_w$ values were 0.86, 0.77, 0.66, 0.56, 0.55, and 0.52, respectively. Compared with other scholars, the citation links of Leydesdorff L, Abramo G, Thelwall M had a larger span between different clusters and had absorbed the knowledge base of multidisciplinary topics. Therefore, these scholars are more likely to become potential forces making changes in the structure of the basic network.

**Table 3** Information of the top 30 authors with the largest △CLw

| Author | $\triangle CL_w$ | Author | $\triangle CL_w$ | Author | $\triangle CL_w$ |
|---|---|---|---|---|---|
| Leydesdorff L | 1.72 | Zhou P | 0.28 | Levitt JM | 0.22 |
| Abramo G | 0.86 | Waltman L | 0.28 | Gonzalez–Teruel A | 0.22 |
| Thelwall M | 0.77 | Persson O | 0.28 | Gomez–Sancho JM | 0.22 |
| Zitt M | 0.66 | Bordons M | 0.28 | Bar–ilan J | 0.22 |
| Yan EJ | 0.56 | Mccarty C | 0.26 | Gazi A | 0.21 |
| Zhang L | 0.55 | Vinkler P | 0.25 | Lancho–Barrantes BS | 0.2 |
| Bornmann L | 0.52 | Boyack KW | 0.24 | Perianes–Rodriguez A | 0.19 |
| Franceschini F | 0.45 | Tang L | 0.23 | Nederhof AJ | 0.18 |
| Mohammadi E | 0.4 | Wu J | 0.22 | Cimenler O | 0.18 |
| Kuan CH | 0.36 | Mutschke P | 0.22 | Wang GB | 0.17 |

**The author´s △Ckl analysis**

We used CiteSpace to analyze the co-citation of the paper's data from 2009 to 2016, and calculated the △Ckl values of different scholars through the centrality dispersion index in the SVA. The distribution of betweenness centrality of nodes in the underlying network varied among the top 30 researchers (Table 4). The centrality dispersion of Franceschet M and Zhang L was greater than 1, which were 1.07 and 1.03, respectively. The centrality dispersions of other scholars such as Bar-Ilan J, Zitt M, Yu G, Egghe L, Kurtz MJ, Bornmann L were 0.92, 0.9, 0.84, 0.82, 0.78, and 0.77, respectively. Compared with other scholars, Franceschet M, Zhang L, Bar-Ilan J, Zitt M had a relatively greater influence on the centrality distribution of the original nodes in the basic knowledge network, and had strong academic influence.

**Table 4** Information of the top 30 authors with the largest △$C_{kl}$

| Author | △Cal | Author | △Cal | Author | △Cal |
|---|---|---|---|---|---|
| Franceschet M | 1.07 | Leydesdorff L | 0.67 | Rafols I | 0.47 |
| Zhang L | 1.03 | Wong CY | 0.6 | Lu K | 0.47 |
| Bar–Ilan J | 0.92 | Persson O | 0.58 | Arencibia–Jorge R | 0.47 |
| Zitt M | 0.9 | Perc M | 0.58 | Yoon B | 0.45 |
| Yu G | 0.84 | Robinson L | 0.55 | Norris M | 0.45 |
| Egghe L | 0.82 | Larsen PO | 0.53 | Brown C | 0.45 |
| Kurtz MJ | 0.78 | Shapira P | 0.51 | Wang GB | 0.44 |
| Bornmann L | 0.77 | Magerman T | 0.49 | Haddow G | 0.43 |
| Upham SP | 0.74 | Kousha K | 0.49 | Moussa S | 0.42 |
| Thelwall M | 0.67 | Sooryamooythy R | 0.48 | Meyer M | 0.42 |

## 4.2 Characteristics of scientific collaboration among potential impact scholars

We used CiteSpace to analyze the data in the field of Information Science from 2009 to 2016, and set LFR=3, LBY=10, e=1.0, Nodes Labeled=5% in the Project panel. A total of 902 nodes and 1031 lines were formed. The network map of author collaboration in the field of Information Science was shown in Figure 2.

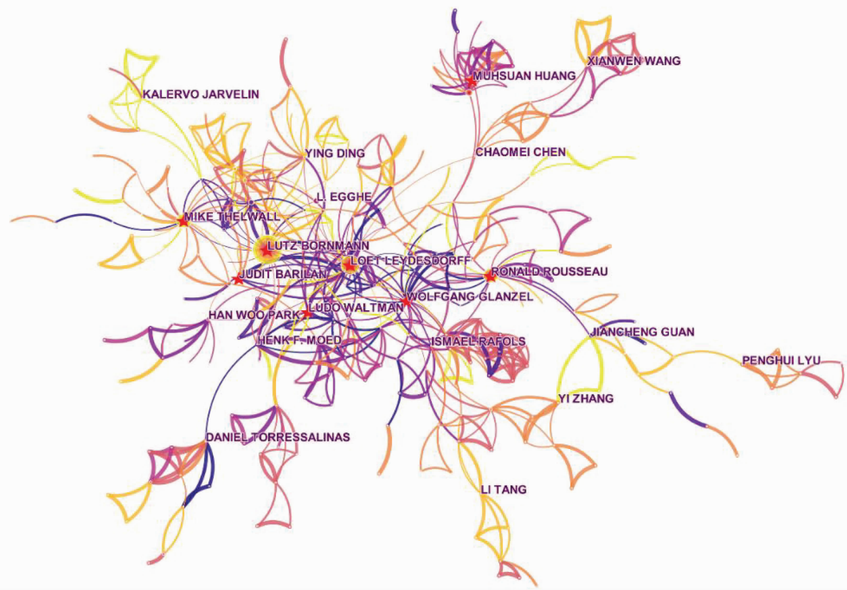


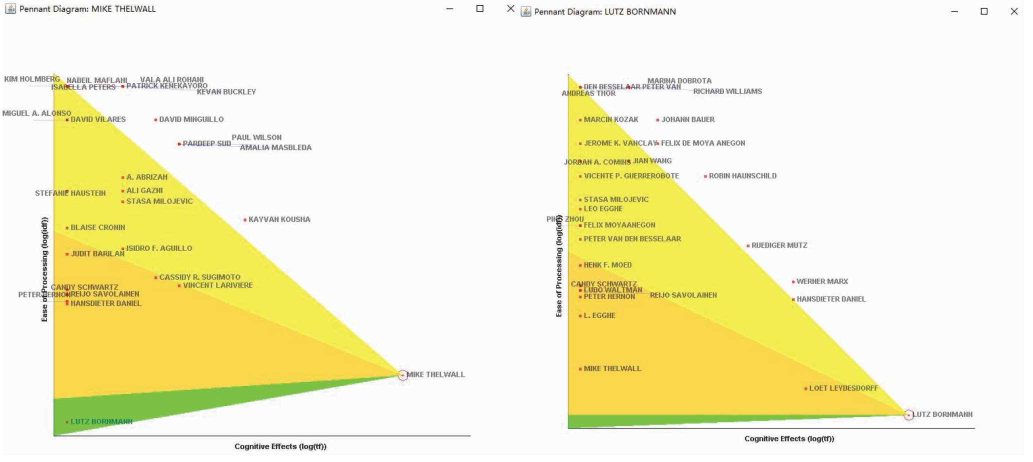

**Figure 2** Author collaboration network in Information Science from 2009 to 2016

We tagged scholars who have been identified as potentially influential in the author collaboration network. We noted scholars who were highly influential in the citation network structure according to the values of different scholars' △M, △CLw, △Ckl, which were represented by five-pointed stars.

Some of the identified pentagram scholars were marked in the author cooperation network in Figure 2. Among them, four scholars, Leydesdorff L, Bornmann L, Thelwall M, and BAR-ILAN J, were among the top 30 scholars with the largest △M, △CLw, and △Ckl. Waltman L had only the top 30 scholars with the largest △CLw value, but its △M and △Ckl values were 3.46 and 0.33, respectively. The △M, △CLw, and △Ckl values of Huang MH were 2.98, 0.13, and 0.04, respectively. The △M, △CLw, and △Ckl values of Rousseau R were 1.11, 0.12, and 0.01, respectively. The △M, △CLw, and △Ckl of Glanzel W values were 3.16, 0.07, and 0.02, respectively. By analyzing the positions of different scholars in the author's cooperation network, it was found that these five-pointed scholars were located in the core positions of different cooperation groups. Scholars with one or two indicators greater than 0 in △M, △CLw, and △Ckl, had not yet formed a large cooperative group with themselves as the core, and are generally located in other large cooperative groups.

In order to further reveal the cooperative characteristics of potential influential scholars, the Pennant Diagram of their cooperation was studied. Pennant Diagram used TF*IDF algorithm. The horizontal coordinate "Cognitive Effects (log(TF))" represents the frequency of the author's presence in the document, and the vertical coordinate "Ease of Processing(log(IDF))" represents the inverse document frequency weight. In addition, White (2007a, 2007b) made a detailed introduction to Pennant Diagram's calculation and significance in Information Science. In this study, in order to use the Pennant Diagram to describe the cooperative relationship between authors, we gave a detailed explanation of the abscissa and ordinate of the Pennant Diagram. For example, in the Pennant Diagram of Thelwall M, the abscissa represented the frequency of cooperation between other scholars and Thelwall M in all of his documents. The closer the horizontal axis is to Thelwall M, the greater the frequency of cooperation between scholars and Thelwall M. The ordinate represents the total number of papers and the papers that the author appears in. The ratio of the number is the logarithm. According to the value of the ordinate, we can see the similarity between the research directions of different scholars and the target scholars. There are three color areas from top to bottom, and the correlation between the three areas and the research direction of the target scholars decreases in turn.

Through the analysis of Pennant Diagram, it can be found that the number of scholars who cooperate with Pennant scholars is much higher than that of other potentially influential non-Pentagram scholars. There was a certain degree of cooperation between different Pentagram scholars, but the frequency of cooperation and similarity of research topics among Pentagram scholars were low. Other potentially influential non-Pentagram scholars were more likely to maintain than Pentagram scholars. High frequency of cooperation and high similarity in research direction. This phenomenon fully illustrated the central position of Pentagram scholars in the author's cooperation network. Figure 3 shows the Pennant Diagram of some pentagram scholars Thelwall M, Bornmann L, Glanzel W, and Waltman L.



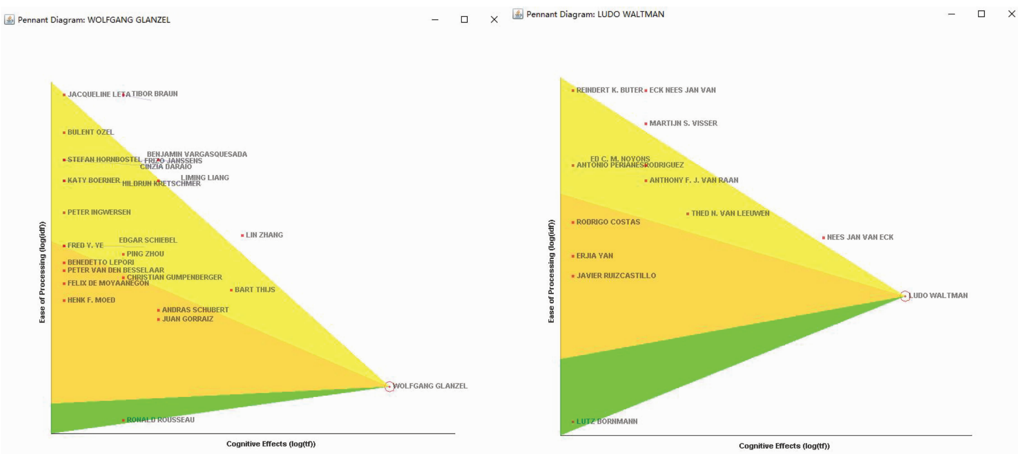



**Figure 3** The Pennant Diagram of the cooperation of some pentagram scholars

# 5 Conclusion and Discussion

Ten core journals were selected to define the field of Information Science by JCA method, and the network knowledge map of researchers' cooperation and co-citation in the field of Information Science from 2009 to 2016 was drawn by CiteSpace. Through the three measurement indexes of Citation Network Structural Variation model, the potential influential researchers and their cooperation characteristics in Information Science were analyzed. The main conclusions of the study include:

(1) Through the co-citation of authors and the △M, △CLw, and △Ckl values, scholars with potential influence under different indexes in the field of Information Science were identified. According to the influence degree of different scholars' △M, △CLw and △Ckl indicators on the author's co-citation network structure, we find out the most potential academically influential Pentagram scholars and non-Pentagonal potential academic influencers in the field of information science. Among them, Pentagram influence scholars include Leydesdorff L, Bornmann L, Thelwall M, Bar-llan J, Waltman L, Huang MH, Rousseau R, etc. These potentially influential scholars had demonstrated high academic influence between 2009-2016 and within the last five-year observation period, which provided important support for the feasibility of identifying potentially influential scholars through SVA.

(2) Through author cooperation and TF*IDF algorithm, we studied the cooperation characteristics of the identified scholars with potentially academic influence, and found that the pentagram scholars were often located in the core position of different cooperation groups in the author cooperation network. Non-Pentagram scholars were generally located in other large cooperative groups, and had not yet formed a large cooperative group with themselves as the core. On the other hand, the study found that the frequency of cooperation and similarity of research topics among Pentagram scholars were low, while other potentially influential non-Pentagram scholars maintained a high frequency of cooperation with Pentagram scholars, and their research directions had a high similarity. In future research, these non-Pentagram scholars will rapidly increase their academic influence through frequent cooperation with Pentagram scholars.

When studying the potential influence of scholars, this study found some interesting phenomena, but there are still some shortcomings in the research process. For example, when identifying potential influential scholars, we initially limited the scholars' names based on their institutions and common email addresses. However, there are still a small number of scholars who may have their institutions changed during this research period. In the follow-up research, we will address this deficiency by sending email consultations. On the other hand, in our research, we found that Pentagram scholars and non-Pentagram scholars have a higher frequency of cooperation and a higher similarity in research direction. However, we have not made in-depth discussions on the specific reasons for this phenomenon. In follow-up research, we will delve into whether this phenomenon is caused by the existence of a large number of mentoring relationships between Pentagram scholars and non-Pentagram scholars.

## References

Ajiferuke, I., & Famoye, F. (2015). Modelling count response variables in informetric studies: Comparison among count, linear, and lognormal regression models. *Journal of Informetrics, 9* (3), 499–513.

Ajiferuke, I., Lu, K., & Wolfram, D. (2010). A comparison of citer and citation–based measure outcomes for multiple disciplines. *Journal of the American Society for Information Science and Technology, 61* (10), 2086–2096.

Bornmann, L. (2014). Do altmetrics point to the broader impact of research? An overview of benefits and disadvantages of altmetrics. *Journal of Informetrics, 8* (4), 895–903.

Chen, C. M. (2012). Predictive effects of structural variation on citation counts. *Journal of the American Society for Information Science and Technology, 63* (3), 431–449.

Chen, C. M. (2017). Science mapping: A systematic review of the literature. *Journal of Data and Information Science, 2* (2), 1–40.

Chen, C. M., Chen, Y., Horowitz, M., Hou, H. Y., Liu, Z. Y., & Pellegrino, D. (2009). Towards an explanatory and computational theory of scientific discovery. *Journal of Informetrics, 3* (3), 191–209.

Contandriopoulos, D., Duhoux, A., Larouche, C., & Perroux, M. (2016). The impact of a researcher´s structural position on scientific performance: An empirical analysis. *Plos One, 11* (8), e0161281.

Corley, E. A., & Sabharwal, M. (2010). Scholarly collaboration and productivity patterns in public administration: Analysing recent trends. *Public Administration, 88* (3), 627–648.

Du, J., Zhang, F., & Tang, X. L. (2014). A discussion on dual measurement of author´s academic influence: The integration of citation influence and cooperative influence. *Journal of the China Society for Scientific and Technical Information, 2014* (4), 388–395.

Egghe, L., & Rousseau, R. (2006). An informetric model for the Hirsch–index. *Scientonetrics, 69* (1), 121–129.

Erdt, M., Nagarajan, A., Sin, S. C., & Theng, Y. L. (2016). Altmetrics: An analysis of the state–of–the–art in measuring research impact on social media. *Scientometrics, 109* (2), 1117–1166.

Franceschet, M., & Costantini, A. (2010). The effect of scholar collaboration on impact and quality of academic papers. *Journal of Informetrics, 4* (4), 540–553.

Galvez, M. A., & Shrum, W. M. (2011). Professional networks, scientific collaboration, and publication productivity in resource–constrained research institutions in a developing country. *Research Policy, 40* (2), 204–216.

Hirsch, J. E. (2005). An index to quantify an individual´s scientific research output. *Proceedings of the National Academy of Sciences of the United States of American, 102* (46), 16569–16572.

Huang, J. S., & Liu, Y. (2013). A study on the cooperation tendency of Chinese university researchers. *Studies in Science of Science, 2013* (11), 1649–1655.

Jin, B. H., Liang, L. M., Rousseau, R., & Egghe, L. (2007). The R– and AR–indices: Complementing the h–index. *Chinese Science Bulletin, 52* (6), 855–863.

Kousha, K., & Thelwall, M. (2015). Web indicators for research evaluation. Part 3: Books and non–standard outputs. *Profesional De La Information, 24* (6), 724–736.

Kumar, K. (2021). Mapping of research output in the Indian veterinary journal through Google Scholar. *Data Science and Informetrics, 1* (1), 81–95.

Leydesdorff, L., & Bornmann, L. (2011). Integrated impact indicators compared with impact factors: An alternative research design with policy implications. *Journal of the American Society for Information Science and Technology, 62* (11), 2133–2146.

Li, S. M., & Li, Z. F. (2018). Knowledge graph in STS field: Based on co–citation analysis of Bernard Prize Winners. *Studies in Science of Science, 2018* (7), 1170–1179.

Liu, X. M. (2018). Research on scholars evaluation from the perspective of author cooperation and journal impact factors. *Information Theory and Practice, 2018* (11), 113–116.

Liu, X. M., Bollen, J., Nelson, M. L., & Van de Sompel, H. (2005). Co–authorship networks in the digital library research community. *Information Processing & Management, 41* (6), 1462–1480.

Ma, R. M., Zhang, H., & Yang, Y. H. (2017). Research on the evaluation of authors´ academic influence from the perspective of weighted citations. *Journal of the China Society for Scientific and Technical Information, 2017* (08), 790–797.

Moed, H. F. (2011). The source normalized impact per paper is a valid and sophisticated indicator of journal citation impact. *Journal of the American Society for Information Science and Technology, 62* (1), 211–213.

Moed, H. F., & Halevi, G. (2015). Multidimensional assessment of scholarly research impact. *Journal of the Association for Information Science and Technology, 66* (10), 1988–2002.

Newman, M. E. J. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences of the United States of America, 98* (2), 404–409.

Newman, M. E. J., Strogatz, S. H., & Watts, D. J. (2001). Random graphs with arbitrary degree distributions and their applications. *Physical Review E, 64* (2), 2.

Ravenscroft, J., Takata, M., Clare, A., & Duma, D. (2017). Measuring scientific impact beyond academia: An assessment of existing impact metrics and proposed improvements. *Plos One, 12* (3), e0173152.

Rodriguez, M. A., & Pepe, A. (2008). On the relationship between the structural and socioacademic communities of a coauthorship network. *Journal of Informetrics, 2* (3), 195–201.

Ronda–Pupo, G. A., & Katz, J. S. (2016a). The power–law relationship between citation–based performance and collaboration in articles in management journals: A scale–independent approach. *Journal of the Association for Information Science and Technology, 67* (10), 2565–2572.

Ronda–Pupo, G. A., & Katz, J. S. (2016b). The scaling relationship between citation–based performance and international collaboration of Cuban articles in natural sciences. *Scientometrics, 107* (3), 1423–1434.

Sebastian, Y., Siew, E. G., & Orimaye, S. O. (2017). Emerging approaches in literature–based discovery: Techniques and performance review. *Knowledge Engineering Review, 32*, 1–35.

Stasa, Milojevic., & Leydesdorff, L. (2013). Information metrics (iMetrics): A research specialty with a socio–cognitive identity?. *Scientometrics, 95* (1), 141–157.

Thelwall, M., & Kousha, K. (2015). Web indicators for research evaluation. Part 1: Citations and links to academic articles from the web. *Profesional De La Information, 24* (5), 587–606.

Thelwall, M., & Kousha, K. (2015). Web indicators for research evaluation. Part 2: Social media metrics. *Profesional De La Information, 24* (5), 607–620.

White, H. D., & McCain, K. W. (1998). Visualizing a discipline: An author co–citation analysis of information science 1972– 1995. *Journal of the American Society for Information Science, 49* (4), 327–355.

White, H. D. (2007a). Combining bibliometrics, information retrieval, and relevance theory, Part 1: First examples of a synthesis. *Journal of the American Society for Information Science and Technology, 58*(4), 536–559.

White, H. D. (2007b). Combining bibliometrics, information retrieval, and relevance theory, Part 2: Some implications for information science. *Journal of the American Society for Information Science and Technology, 58* (4), 583–605.

Yan, E. J., & Ding, Y. (2009). Applying centrality measures to impact analysis: A coauthorship network analysis. *Journal of the American Society for Information Science and Technology, 60* (10), 2107–2118.

Yang, S., & Wang, F. (2015). Visualizing information science: Author direct citation analysis in China and around the world. *Journal of Informetrics, 9* (1), 208–225.

Zhao, D. Z., & Strotmann, A. (2014).The knowledge base and research front of information science 2006–2010: An author cocitation and bibliographic coupling analysis. *Journal of the Association for Information Science and Technology, 65* (5): 995–1006.