Applying Centrality Measures to Impact Analysis: A Coauthorship Network Analysis

Erjia Yan and Ying Ding
School of Library and Information Science, Indiana University, 1320 East 10th Street, Bloomington, IN 47405-3907. E-mail: {eyan, dingying}@indiana.edu

Many studies on coauthorship networks focus on network topology and network statistical mechanics. This article takes a different approach by studying micro-level network properties with the aim of applying centrality measures to impact analysis. Using coauthorship data from 16 journals in the field of library and information science (LIS) with a time span of 20 years (1988–2007), we construct an evolving coauthorship network and calculate four centrality measures (closeness centrality, betweenness centrality, degree centrality, and PageRank) for authors in this network. We find that the four centrality measures are significantly correlated with citation counts. We also discuss the usability of centrality measures in author ranking and suggest that centrality measures can be useful indicators for impact analysis.

Introduction

Social network analysis has developed as a specialty in parallel with scientometrics since the 1970s. Examples include Hubbell's measure of sociometric status, Bonacich and Freeman's measure of centrality, Coleman's measure of power, and Burt's measure of prestige (Friedkin, 1991). The last decade has witnessed a new movement in the study of social networks, with the main focus moving from the analysis of small networks to those with thousands or millions of vertices and with a renewed attention to the topology and dynamics of networks (Newman, 2001a). This new approach largely has been driven by improved computing technologies that allow us to gather and analyze data in large scales, and such technologies make it possible to uncover the generic properties of social networks (Albert & Barabási, 2002).

The coauthorship network, an important type of social network, has been intensively studied in this movement (Newman, 2001a,b; Barabási, Jeong, Neda, Ravasz, Schubert, & Vicsek, 2002; Nascimento, Sander, & Pound, 2003; Kretschmer, 2004; Liu, Bollen, Nelson, & Sompel, 2005; Yin, Kretschmer, Hanneman, & Liu, 2006; Vidgen, Henneberg, & Naude, 2007; Rodriguez & Pepe, 2008). Most of these studies focus on macro-level network properties; that is, they seek to describe a social network's global characteristics (Liu et al., 2005) and conceptualize its overall structural features. Commonly used measures of macro-level network properties are diameter, mean distance, components, clusters coefficient, etc. Yet not enough attention is paid to the micro-level structure, and therefore the properties of individual network actors in social structures, such as power, stratification, ranking, and inequality, receive little scrutiny (Wasserman & Faust, 1994). Such an approach zooms in to capture the features of the individual actors in a network along with consideration of the topology of the network. This article aims to study a social network's micro-level structure by applying centrality measures to a coauthorship network. We attempt to identify (1) the extent to which different centrality measures can describe the authors' career paths (Cronin & Meho, 2007) through an evolving network; (2) the distributions of centrality and their correlations with citation counts; and (3) the ways in which characteristics of centrality measures can be incorporated into impact evaluation. Finally, we also discuss the strengths and limitations of centrality measures.

Related Studies

Centrality analysis is not new to sociology. In a groundbreaking piece, Freeman (1977) developed a set of measures for centrality based on betweenness. In a follow-up article, Freeman (1979) proposed four concepts of centrality in a social network, which have been developed into degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Some influential research on this topic includes: the relationship between centrality and power (Hackman, 1985; Bonacich, 1987; Ibarra, 1993; Ibarra & Andrews, 1993); the relationship between salience and psychological centrality (Stryker & Serpe, 1994); the influence of centrality on choices and behaviors (Verplanken & Holland, 2002); the role of centrality

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within family (Crosbieburnett, 1984), organization networks (Boje & Whetten, 1981; Paullay, Alliger, & Stoneromero, 1994), and groups and classes (Everett & Borgatti, 1999).

Centrality has also been applied to journal impact analysis. Using journal data from the Institute for Scientific Information (ISI), Bollen, Rodriguez, & van de Sompel (2006) demonstrated how a weighted version of the PageRank algorithm can obtain a metric that reflects prestige. They contrasted the rankings of journals according to the ISI impact factor and their weighted PageRank and discovered that the two metrics both have overlaps and differences. Leydesdorff (2007) applied betweenness centrality to 7,379 journals included in the Journal Citation Reports and found that betweenness centrality indicates journal interdisciplinarity. Dellavalle, Schilling, Rodriguez, van de Sompel, & Bollen (2007) studied dermatology journals using a weighted PageRank algorithm that assigned greater weight to citations originating in more frequently cited journals. They found that the weighted PageRank algorithm provided a more refined measure of journal status because it considers the impact of citing journals.

As for coauthorship networks, several studies also have applied centrality measures to coauthorship network analysis. Mutschke (2003) employed centrality to the coauthorship network of digital libraries research. Liu et al. (2005) applied centrality analysis to coauthorship of the Joint Conference on Digital Libraries (JCDL) research community and discovered that betweenness centrality performed best among the three centrality measures when comparing the results with the ranking of JCDL program committee membership. Estrada & Rodriguez-Velazquez (2005) proposed a new centrality measure that characterizes the participation of each node in all of the subgraphs in a network. They found that this centrality measure displayed useful and desirable properties, such as clearly ranked nodes and scale-free characteristics. Chen (2006) used betweenness centrality to highlight potential pivotal points of paradigm shifts in scientific literature over time. Yin et al. (2006) applied three centrality measures to the COLLNET community coauthorship network. Vidgen et al. (2007) applied five centrality measures (degree, betweenness, closeness, eigenvector, and flow betweenness) and structural holes in order to rank an information system community. Liu et al. (2007) applied betweenness centrality to the weighted coauthorship network of nature science research in China.

Proposed by Garfield in the 1960s, citation has been a formative instrument of scientometrics and a subject of study for several decades (Leydesdorff, 1998). Although the utility of citation is still debated, it presently is one of the most successful scientific impact evaluation tools. Because it is so prevalent, whenever a new scientific evaluation indicator is proposed we can always see its origination from citation, as demonstrated by impact factor (Hirst, 1978), Web impact factor (Ingwersen, 1998), and *h*-index (Hirsch, 2005). Additionally, the results of a new indicator often are compared with citation. Examples include Y-factor (Bollen et al., 2006), betweenness centrality for journals (Leydesdorff, 2007), etc. Following this tradition, this study also compares the results of centrality measures with citation counts through correlation analysis; the comparison will be discussed in the following sections.

Methodology

Centrality Measures

In this study we apply three classic centrality measures (degree centrality, closeness centrality, and betweenness centrality) and PageRank (which is a variant of eigenvector centrality) to the coauthorship network.

Degree centrality. Degree centrality equals the number of ties that a vertex has with other vertices. The equation for this measure is as follows, where $d(n_i)$ is the degree of n_i:

$$C_D(n_i) = d(n_i) \tag{1}$$

Generally, vertices with a higher degree or more connections are more central to the structure and tend to have a greater ability to influence others.

Closeness centrality. A more sophisticated centrality measure is closeness (Freeman, 1979). It emphasizes the distance of a vertex to all others in the network by focusing on the geodesic distance from each vertex to all others. According to Yin et al. (2006), closeness is a metric of "how long it will take information to spread from a given vertex to others in the network" (p. 1603). Closeness centrality focuses on the extent of influence over the entire network. In the following equation, $C_c(n_i)$ is the closeness centrality and $d(n_i,n_j)$ is the distance between two vertices in the network:

$$C_{\mathrm{c}}(n_i) = \sum_{i=1}^{N} \frac{1}{d(n_i, n_j)} \tag{2}$$

Betweenness centrality. Betweenness centrality is based on the number of shortest paths passing through a vertex. Vertices with high betweenness connect different groups. In the following formula, g_{jik} is all geodesics linking node *j* and node *k* which pass through node *i*; g_{jk} is the geodesic distance between the vertices of *j* and *k*:

$$C_B(n_i) = \sum_{j,k \neq i} \frac{g_{jik}}{g_{jk}} \tag{3}$$

In social networks, vertices with high betweenness are "pivot points of knowledge flow in the network" (Yin et al., 2006, p. 1603). For coauthorship networks, vertices with high betweenness connect authors who share similar research interest. Therefore, authors with high betweenness usually engage in research of different fields and thus show interdisciplinarity.

According to Scott (2000), Burt has described betweenness in terms of structural holes, which are the absence of

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tie in a triad. Therefore, both betweenness and structural holes measure the information flow in networks. However, the differences between the two lie in their perspectives: betweenness focuses on actors (i.e., the importance of an actor to others' communication), while structural holes focus on ties (i.e., the importance of a tie to actors' communication). Although structural holes (as a metric) also can be reflected through the aggregate constraint of each tie (Nooy, Mrvar, & Batagelj, 2005), it still is considered a metric of ties rather than a measure of node centrality. Since we are focusing on evaluating the individual nodes of the graph, structural holes consequently are not applied.

Eigenvector centrality and PageRank. Eigenvector is based on the principle that the importance of a node depends on the importance of its neighbors. The prestige x_i of node i is proportional to the sum of the prestige of the neighboring nodes pointing to it (Perra & Fortunato, 2008):

$$\lambda x_i = \sum\nolimits_{j:j\to i} x_j = \sum\nolimits_{j} A_{ji} x_j = (A' x)_i \tag{4}$$

where x_i is the i component of the eigenvector of the transpose of the adjacency matrix with eigenvalue λ. PageRank, on the other hand, is derived from the influence weights proposed by Pinski & Narin (1976), and is formally formulated by Page & Brin (1998), who developed a method for assigning a universal rank to Web pages based on a weight-propagation algorithm called PageRank. A page has high rank if the sum of the ranks of its backlinks is high. This idea is captured in the PageRank formula as follows:

$$PR(p) = \frac{(1-d)}{N} + d \sum_{i=1}^{k} \frac{PR(p_i)}{C(p_i)} \tag{5}$$

where N is the total number of pages on the Web, d is a damping factor, $C(p_i)$ is the outdegree of p_i, and p_i denotes the inlinks of p. PageRank is, in fact, the principal eigenvector of the transition matrix M:

$$M_{ij} = \frac{(1-d)}{N} + d \frac{1}{C(p_i)} A_{ji} \tag{6}$$

and usually is determined by repeatedly multiplying the matrix M by an arbitrary vector until all the entries of the resulting vector are stable (Perra & Fortunato, 2008). Based on this, we consider PageRank to be a variant of eigenvector centrality, and therefore we classify it as a centrality measure in this study. Actors in the PageRank of Web information retrieval systems are Web pages, and actors in the PageRank of coauthorship networks are authors. If author A coauthors with author B, this is similar to endowing one credit to B; if B has three collaborators, then each of her/his collaborators will have a third of B's credit; the procedure continues in this way until all authors have stable PageRank values. So PageRank does not merely count how many collaborators an author has, but it also considers the impacts of those collaborators.

Data Processing

We chose the top 16 LIS journals based on (1) ratings by deans and directors of North American programs accredited by the ALA (Nisonger & Davis, 2005), and (2) Journal Citation Reports (JCR) data for the years 1988–2007. We excluded non-LIS journals from the rankings, such as *MIS Quarterly, Journal of the American Medical Informatics Association, Information Systems Research, Information & Management*, and *Journal of Management Information Systems*. Meanwhile, since some journals had changed their names during this time period, we also included these older-titled journals in our dataset (shown in parentheses below). The 16 journals are: *Annual Review of Information Science and Technology; Information Processing and Management; Scientometrics; Journal of the American Society for Information Science and Technology (Journal of the American Society for Information Science); Journal of Documentation; Journal of Information Science; Information Research; Library and Information Science Research; College and Research Libraries; Information Society; Online Information Review (Online and CD-ROM Review; On-Line Review); Library Resources and Technical Services; Library Quarterly; Journal of Academic Librarianship; Library Trends*; and *Reference and User Services Quarterly*.

We downloaded the 20-year data of these 16 journals from the Web of Science database. There are a total of 22,380 documents, from which we just focus on articles and review articles. The number of these records is 10,344 (the remaining material largely consists of book reviews and editorial material).

Results and Analysis

An Overview

After downloading the data from the ISI Web of Science, we extracted the coauthorship network using Network Workbench (NWB, 2006). Because some authors used middle initials for some of their articles but not others, we combined the same authors manually based on their affiliation information (e.g., we combined "Meho, L" and "Meho, LI" as one author in the network).

A component of a graph is a subset in which there is a path between a node and any other node of this subset (Nooy et al., 2005). A coauthorship network consists of many disconnected components, and usually we focus on the largest component. The distance from vertex u to vertex v is the length of the geodesic from u to v. As defined formally by Watts & Strogatz (1998) and informally by Milgram (1967), many social networks display structures where most individuals are at very few degrees of distance from one another. The summary statistics for the LIS coauthorship network are shown in Table 1.

There are 10,579 authors in this network, in which the average author writes 2.40 articles, the average article has 1.80 authors, and the average author collaborates with 2.24 other authors. These are relatively low values compared to

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TABLE 1. Summary statistics for LIS coauthorship network.

	Values
Number of papers	10,344
Number of authors	10,579
Papers per author	2.40
Authors per paper	1.80
Mean collaborators	2.24
Largest component	20.77%
Mean distance	9.68

TABLE 2. Properties of the evolving LIS coauthorship network from 1988 to 2007.

Year	Number of authors	Number of papers	Mean collaborators	Largest component Size	Largest component Ratio%	Mean distance
1988–1992	2,262	2,039	1.70	46	2.26	2.49
1988–1997	4,357	4,234	1.76	91	2.15	5.30
1988–2002	6,941	6,891	1.91	646	9.37	9.54
1988–2007	10,579	10,344	2.24	2197	21.24	9.68

the coauthorship networks of biology and physics as constructed by Newman (2001b), who found that papers per author, authors per paper, and mean collaborators for the biology coauthorship network are 6.4, 3.75, and 18.1, respectively; for the physics coauthorship network, the values are 5.1, 2.53, and 9.7. This results from two factors. First, LIS scientists are less collaborative than biologists and physicists. In our dataset, only 39 authors have collaborated with more than 18 authors, which is the median number of collaborators for the biology coauthorship network. Second, biologists and physicists tend to collaborate more frequently and more widely due to their research requirements. It is not unusual for papers published in biological journals to have more than 10 authors, but this is quite rare for LIS articles.

The number of papers and authors of LIS coauthorship network increases gradually. The two curves fit $y = 363.95t^{1.08}$ and $y = 492.00t^{0.98}$ and (time: t = 1, 2, 3, ...) respectively, with $R^2 = 0.9973$ and $R^2 = 0.9932$. This result indicates that the number of papers and authors can be expected to increase approximately with these curves in the coming years. Their evolving graphs are showing in Figure 1.

Similar to observations from previous studies on coauthorship networks, the LIS coauthorship network is not a single connected graph. The largest component of the network has 2,197 authors, containing about 20% of the total authors in the network. Nascimento et al. (2003) reported that the largest component in SIGMOD's coauthorship graph contains about 60% of all authors. In the four coauthorship networks studied by Newman (2001b), MedLine has the largest component, with 92.6% of all the authors, while NCSTRL has the smallest largest component, containing 57.2% of all authors. After some comparison studies on coauthorship networks, Kretschmer (2004) suggests that the largest components usually have a ratio of more than 40% of all the authors. Our research only includes 16 journals, which potentially cut some collaboration ties between authors. Meanwhile, the nature of the discipline under study also may affect this ratio. Generally, more authors are involved in experimental research; accordingly, disciplines like biology and physics would possess a bigger portion of the largest component.

Table 2 shows the properties of the evolving LIS coauthorship network. Each author, on average, has more collaborators as time progresses: from 1.70 collaborators in the 1988–1992 period to 2.24 in the 1988–2007 period. The increased mean collaborator signifies that authors have collaborated more extensively in recent years, indicating a shift in the LIS field.

The values of the largest component exhibit some diverse characteristics. In their study on mathematics and neuroscience coauthorship networks, Barabási et al. (2002) found that the mean distance of the mathematics coauthorship network decreased from 16 in 1991 to 9 in 1998, and the mean distance of the neuroscience coauthorship network decreased from 10 in 1991 to 6 in 1998. Leskovec, Backstrom, Kumar, & Tomkins (2008) found that in large social networks (e.g., FLICKR, ANSWERS, and LINKEDIN) the diameters reach the maximum value of 10 when the network has around

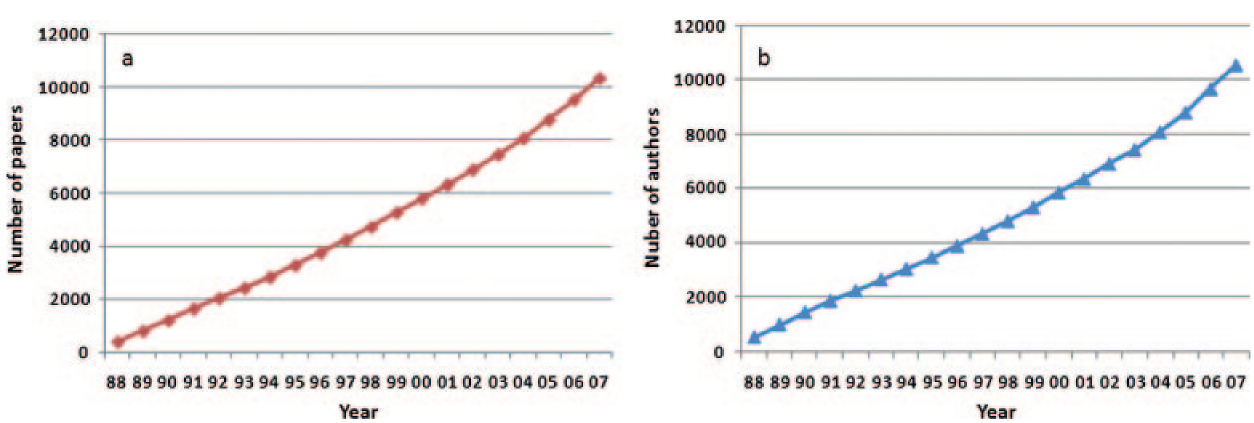

FIG. 1. Yearly accumulative distribution of papers (a) and authors (b).

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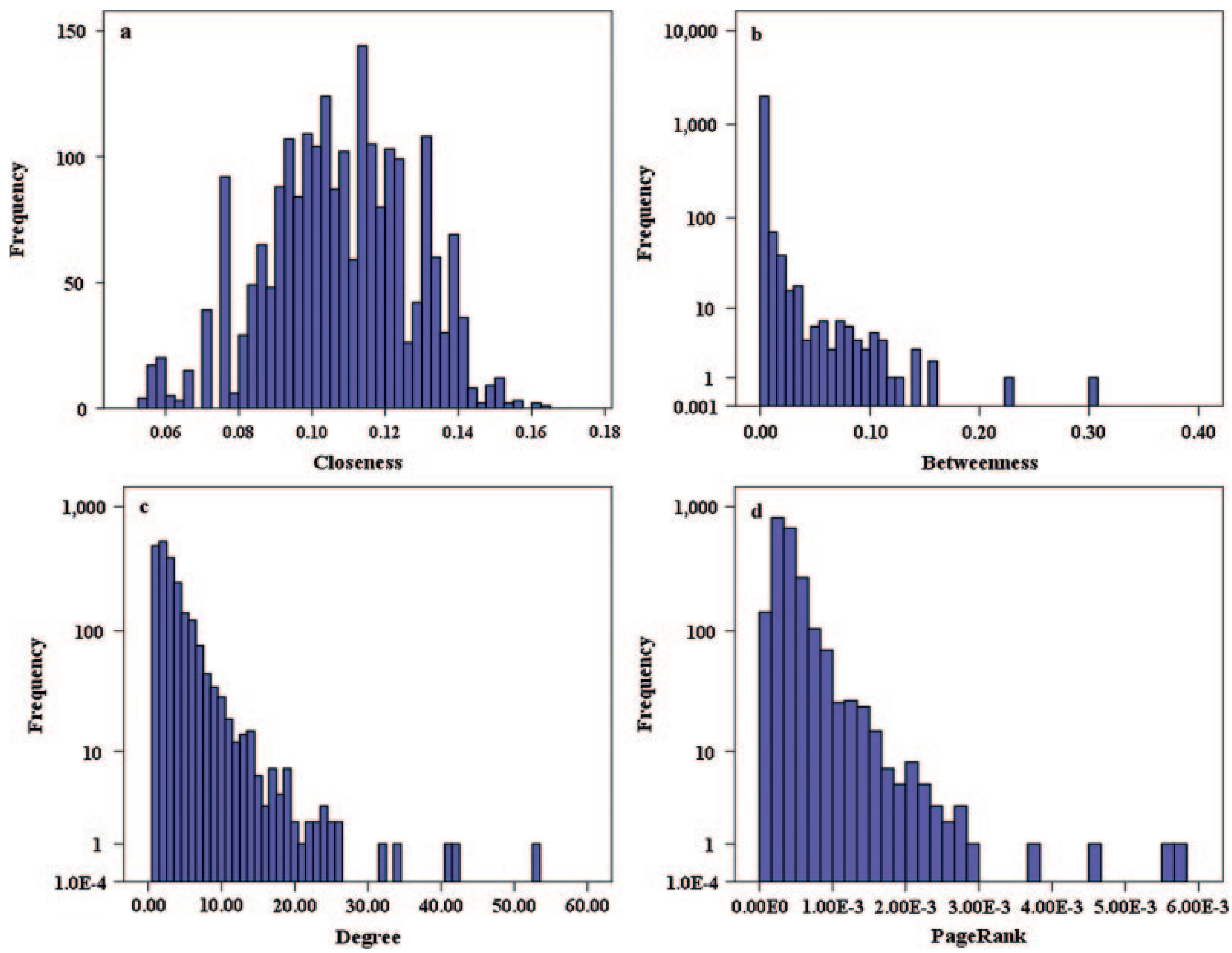

FIG. 2. Frequency distribution of closeness (a), betweenness (b), degree (c), and PageRank (d).

50,000 nodes and then decrease to around 7.5. However, the mean distance of the LIS coauthorship network increased from 2.49 in 1992 to 9.68 in 2007, but it has not yet reached its maximum value. The discrepancy is due to the fact that more new authors are involved in this field each year, but their collaboration pattern is simple and the scope of the collaboration is limited. Although LIS is becoming increasingly more collaborative, the field has not arrived at its "phase transition" (Barabási, 2003). If the mean distance were decreasing, one could conclude that this network has attained its phase transition where authors collaborate with each other much more frequently and more widely.

Applying Centrality Measures to Author Ranking

Historically, most studies on coauthorship network analysis focus on the overall topology of networks, whereas little research has been done regarding their individual properties, and even less work has been completed on the relationship between citations and centrality measures. In this study we calculate four centrality measures for authors in the largest component. Their frequency distributions are shown in Figure 2.

There is a strong inverse relationship between centrality values (for betweenness, degree, and PageRank) and their frequencies, which may be modeled as power-law distribution (with $R^2 = 0.8028$, 0.9185, and 0.7326, respectively). These values indicate that most authors have low centrality values while only a few authors have high centrality values. On the other hand, the distribution of closeness centrality follows the normal curve. The relationship between degree centrality and its frequency probability matches the curve: $p(k) = 1.1778k^{-2.1514}$ with $R^2 = 0.9185$, which may indicate that this coauthorship network has scale-free character (Barabási & Albert, 1999). This result is also consistent with Price's (1965) network of citations. He quoted a value of $\alpha = 2.5$ to 3 for the exponent of his network. Other relevant research on scale-free networks also confirmed Price's assumption (Newman, 2003).

Tables 3–6 show the top 30 authors based on closeness centrality, betweenness centrality, degree centrality, and PageRank as calculated with the coauthorship networks of 1988–1992, 1988–1997, 1988–2002, and 1988–2007, respectively. Authors appearing consecutively in the four time periods are marked in bold font, and authors appearing in three time periods are marked in italic font.

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TABLE 3. Top 30 authors based on closeness centrality.

R	1988–1992	1988–1997	1988–2002	1988–2007	R	1988–1992	1988–1997	1988–2002	1988–2007
1	**Willett, P**	**Willett, P**	*Spink, A*	*Spink, A*	16	Rohde, NF	Rao, IKR	Ozmutlu, HC	Kantor, P
2	**Wood, FE**	*Bawden, D*	*Ellis, D*	**Willett, P**	17	Miquel, JF	Walker, S	Greisdorf, H	Kretschmer, H
3	*Bawden, D*	**Wood, FE**	Ford, N	*Ellis, D*	18	Straub, D	*Saracevic, T*	Robins, D	*Bawden, D*
4	Cringean, JK	Beaulieu, M	*Losee, RM*	Ford, N	19	Beath, CM	Robertson, S	Ozmutlu, S	Jansen, BJ
5	Manson, GA	*Ellis, D*	**Willett, P**	Wilson, TD	20	Zeb, A	Haas, SW	Goodrum, A	Hernon, P
6	Lynch, MF	Lynch, MF	Wolfram, D	*Saracevic, T*	21	Mhashi, M	Rada, R	He, SY	Leydesdorff, L
7	Lunin, LF	Cringean, JK	Furner, J	Zhang, J	22	Michailidis, A	Dillon, M	Furnerhines, J	Bishop, N
8	Rada, R	Robertson, AM	Wilson, TD	Wolfram, D	23	Mussio, P	*Rousseau, R*	Bookstein, A	Rowlands, I
9	Delia, G	Manson, GA	Foster, A	Furner, J	24	Padula, M	*Cool, C*	Rasmussen, EM	Tang, R
10	*Rousseau, R*	*Borgman, CL*	*Saracevic, T*	*Losee, RM*	25	Bordogna, G	Meadow, CT	Haas, SW	*Cool, C*
11	Lancaster, FW	*Losee, RM*	Zhang, J	Rasmussen, EM	26	Carrara, P	Case, DO	**Wood, FE**	Vakkari, P
12	Naldi, F	Bookstein, A	Jansen, BJ	Jarvelin, K	27	Bauin, S	Rice, RE	*Borgman, CL*	Abels, EG
13	Courtial, JP	Meadows, AJ	*Cool, C*	Thelwall, M	28	*Borgman, CL*	Egghe, L	Allen, D	**Wood, FE**
14	Zimmerman, JL	*Spink, A*	Cole, C	*Rousseau, R*	29	Laville, F	Lancaster, FW	Hall, K	Bjorneborn, L
15	Cooper, M	Lunin, LF	Schamber, L	Foster, A	30	van Raan, AFJ	Belkin, NJ	Cox, D	Vaughan, L

TABLE 4. Top 30 authors based on betweenness centrality.

R	1988–1992	1988–1997	1988–2002	1988–2007	R	1988–1992	1988–1997	1988–2002	1988–2007
1	**Willett, P**	*Losee, RM*	*Spink, A*	**Willett, P**	16	Glanzel, W	Fox, EA	Iivonen, M	Kretschmer, H
2	Lunin, LF	*Bookstein, A*	*Losee, RM*	*Spink, A*	17	*Bookstein, A*	*Lancaster, FW*	*Saracevic, T*	Tang, R
3	Wood, FE	**Willett, P**	**Borgman, CL**	Chowdhury, GG	18	Mussio, P	Belkin, NJ	White, MD	**Borgman, CL**
4	Rada, R	*Spink, A*	Furner, J	Lynch, MF	19	Padula, M	Liebscher, P	Ford, N	Meyer, M
5	*Bawden, D*	**Rousseau, R**	**Willett, P**	Zhang, J	20	Bauin, S	Miquel, JF	Wang, PL	Rowlands, I
6	Courtial, JP	*Saracevic, T*	*Bookstein, A*	**Rousseau, R**	21	Schubert, A	Allen, B	Beaulieu, M	Wolfram, D
7	Naldi, F	Rao, IKR	Zhang, J	*Lancaster, FW*	22	Case, DO	*Wood, FE*	Tenopir, C	Vakkari, P
8	**Rousseau, R**	Beaulieu, M	Ellis, D	Bishop, N	23	Meadows, AJ	Meadow, CT	Oddy, RN	Smith, A
9	Miquel, JF	**Borgman, CL**	Haas, SW	Hernon, P	24	Winterhager, M	Tibbo, HR	Bishop, N	*Bawden, D*
10	*Lancaster, FW*	*Bawden, D*	Korfhage, RR	Ellis, D	25	Turner, WA	Pettigrew, KE	Mcclure, CR	Fox, EA
11	van Raan, AFJ	Meadows, AJ	Myaeng, SH	Thelwall, M	26	Dillon, M	Cronin, B	Nahl, D	*Losee, RM*
12	**Borgman, CL**	Haas, SW	Wolfram, D	*Saracevic, T*	27	Woodsworth, A	Dillon, M	Smith, M	Foo, S
13	Laville, F	Lunin, LF	**Rousseau, R**	Leydesdorff, L	28	Braam, RR	Kantor, P	Rao, IKR	Jarvelin, K
14	Nederhof, AJ	Rada, R	Meho, LI	Morris, A	29	Moed, HF	Cool, C	Yitzhaki, M	Rasmussen, EM
15	Egghe, L	Abels, EG	Sonnenwald, DH	Kantor, P	30	Braun, T	Walker, S	Rice, RE	Furner, J

TABLE 5. Top 30 authors based on degree centrality.

R	1988–1992	1988–1997	1988–2002	1988–2007	R	1988–1992	1988–1997	1988–2002	1988–2007
1	**Willett, P**	**Willett, P**	**Rousseau, R**	**Rousseau, R**	16	Carrara, P	*Bookstein, A*	*Miquel, JF*	Kostoff, RN
2	*Rada, R*	**Rousseau, R**	**Willett, P**	**Willett, P**	17	van Raan, AFJ	Beaulieu, M	Choi, KS	Zhang, J
3	**Rousseau, R**	**Lancaster, FW**	Oppenheim, C	Oppenheim, C	18	*Meadows, AJ*	Walker, S	Ellis, D	Glanzel, W
4	**Lancaster, FW**	*Rada, R*	Chen, HC	Spink, A	19	*Bookstein, A*	van Raan, AFJ	Saracevic, T	Gupta, BM
5	**Courtial, JP**	**Courtial, JP**	Spink, A	Ford, N	20	Lunin, LF	Hancockbeaulieu, M	Gibb, F	Croft, WB
6	*Wood, FE*	*Meadows, AJ*	**Lancaster, FW**	Leydesdorff, L	21	Gagliardi, I	Glanzel, W	*Belkin, NJ*	*Belkin, NJ*
7	Naldi, F	Padula, M	**Borgman, CL**	**Borgman, CL**	22	Merelli, D	Braun, T	Morris, A	Choi, KS
8	**Bawden, D**	**Borgman, CL**	**Courtial, JP**	**Lancaster, FW**	23	Vanhoutte, A	Schubert, A	*Bookstein, A*	Zobel, J
9	*Miquel, JF*	*Miquel, JF*	*Rada, R*	Jarvelin, K	24	Hamers, L	Budd, JM	Robertson, S	Nicholas, D
10	Mussio, P	*Cronin, B*	Ford, N	Thelwall, M	25	Hemeryck, Y	Chen, HC	Croft, WB	Debackere, K
11	Padula, M	**Bawden, D**	*Cronin, B*	Kantor, P	26	Herweyers, G	Woodsworth, A	*Wood, FE*	Miller, D
12	**Borgman, CL**	*Wood, FE*	*Moed, HF*	*Cronin, B*	27	Janssen, M	Haas, SW	Tijssen, RJW	**Bawden, D**
13	Bauin, S	Saracevic, T	*Meadows, AJ*	*Moed, HF*	28	Keters, H	*Belkin, NJ*	Frieder, O	Tenopir, C
14	Woodsworth, A	*Fox, EA*	Gupta, BM	**Courtial, JP**	29	Schubert, A	Allen, B	Wolfram, D	Kelly, D
15	Bordogna, G	*Moed, HF*	**Bawden, D**	*Fox, EA*	30	Lester, J	Hernon, P	*Fox, EA*	Huntington, P

A few authors are ranked highly through all four periods between 1988 and 2007. Examples include: closeness centrality for Willett, P (1-1-5-2; the formatting corresponds to 1st in 1988–1992, 1st in 1988–1997, 5th in 1988–1997, and 2nd in 1988–2007); betweenness centrality for Willett, P (1-3-5-1); betweenness centrality for Borgman, CL (12-9-3-18); betweenness centrality for Rousseau, R (8-5-13-6); degree centrality and PageRank for Willett, P (1-1-2-2;

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TABLE 6. Top 30 authors based on PageRank.

R	1988–1992	1988–1997	1988–2002	1988–2007	R	1988–1992	1988–1997	1988–2002	1988–2007
1	**Willett, P**	**Willett, P**	**Rousseau, R**	*Oppenheim, C*	16	Buttlar, L	**Bookstein, A**	Ford, N	Thelwall, M
2	**Lancaster, FW**	**Lancaster, FW**	**Willett, P**	**Rousseau, R**	17	Metz, P	Saracevic, T	*Moed, HF*	**Meadows, AJ**
3	**Rousseau, R**	**Rousseau, R**	*Oppenheim, C*	**Willett, P**	18	Garg, KC	*Croft, WB*	Tenopir, C	*Hernon, P*
4	*Wood, FE*	*Rada, R*	**Lancaster, FW**	Spink, A	19	Yatesmercer, PA	Williams, ME	*Budd, JM*	**Courtial, JP**
5	*Rada, R*	**Meadows, AJ**	Spink, A	Jarvelin, K	20	Schubert, A	Chen, HC	**Bookstein, A**	*Moed, HF*
6	**Courtial, JP**	**Cronin, B**	Chen, HC	*Leydesdorff, L*	21	Bauin, S	*Morris, A*	Harter, SP	*Croft, WB*
7	**Meadows, AJ**	**Courtial, JP**	**Cronin, B**	**Cronin, B**	22	Naldi, F	Voigt, K	*Leydesdorff, L*	Kostoff, RN
8	**Borgman, CL**	*Budd, JM*	**Meadows, AJ**	**Lancaster, FW**	23	*Budd, JM*	Wolfram, D	Wolfram, D	Kling, R
9	**Bawden, D**	**Borgman, CL**	**Borgman, CL**	Ford, N	24	Harris, RM	Frieder, O	Williams, ME	Tenopir, C
10	**Bookstein, A**	**Bawden, D**	**Courtial, JP**	Zhang, J	25	Case, DO	Rice, RE	*Hernon, P*	Mcclure, CR
11	**Cronin, B**	*Wood, FE*	*Rada, R*	**Borgman, CL**	26	Vizinegoetz, D	Delia, G	*Wood, FE*	Choi, KS
12	van Raan, AFJ	*Oppenheim, C*	**Bawden, D**	Zobel, J	27	Saracevic, T	van Raan, AFJ	*Croft, WB*	Glanzel, W
13	Miquel, JF	*Hernon, P*	Gupta, BM	*Morris, A*	28	Spangenberg, JFA	*Leydesdorff, L*	Frieder, O	**Bookstein, A**
14	Pravdic, N	*Moed, HF*	*Morris, A*	Gupta, BM	29	Nederhof, AJ	Metz, P	Voigt, K	Connaway, LS
15	Tague, J	Harter, SP	Ingwersen, P	**Bawden, D**	30	Oberg, LR	Dillon, M	Dilevko, J	Fox, EA

1-1-2-3); degree centrality and PageRank for Rousseau, R (3-2-1-1; 3-3-1-2); and degree centrality and PageRank for Lancaster, FW (4-3-6-8; 2-2-4-8). This 20-year period is a prolific time for these authors: they collaborated frequently (degree centrality), productively (PageRank), widely (closeness centrality), and diversely (betweenness centrality).

Some authors have collaborated more actively in recent years. Spink, A only published one article during 1988–1992 (according to this dataset), and as a result, her centrality for that period ranked low—only 224 for closeness centrality and 797 for degree centrality. Nevertheless, in the past 15 years she published 53 articles and collaborated with 34 authors. Her results for closeness centrality and degree centrality are 224-43-1-1 and 797-105-5-4. Similar situations can also be observed with Ellis, D (closeness centrality: 2054-5-2-3); Saracevic, T (closeness centrality: 170-18-10-6; betweenness centrality: 47-6-17-12); Losee, RM (closeness centrality: 313-11-4-10); Cronin, B (degree centrality: 62-10-11-12); Moed, HF (degree centrality: 175-15-12-13); Fox, EA (degree centrality: 410-14-30-15); Oppenheim, C (PageRank: NA-12-3-1); Leydesdorff, L (PageRank: 58-28-22-6); and Morris, A (PageRank: 44-21-14-13).

Meanwhile, some authors are less collaborative in this field in recent years, which may be caused by switching their research directions or other personal affairs like retirement. Most LIS articles published by Rada, R, for instance, are circa 1985–1995, but after 1995 his publications appear more frequently in computer science journals. Thus, his degree centrality and PageRank have decreased since then: 2-4-9-1198 for degree centrality and 5-4-11-1850 for PageRank. Most articles published by Wood, EF date from the 1980s to 1990s, and, as a result his centrality rankings are on the decline: 2-3-28-28 for closeness centrality, 3-14-54-168 for betweenness centrality, 6-12-26-69 for degree centrality, and 4-11-26-40 for PageRank. Other examples of a recent decline in collaboration include Cringean, JK (closeness centrality: 4-7-51-37) and Lunin, LF (betweenness centrality: 2-13-137-890).

Furthermore, new forces in this field may also be identified. A typical example is Thelwall, M: all of his articles are published after 2000, and thus, he does not have centrality values for the first two periods and very low values for 1988–2002. Nevertheless, his centrality for 1988–2007 is quite high; all of the values are in the top 30: 13th for closeness centrality, 11th for betweenness centrality, 10th for degree centrality, and 16th for PageRank. Other examples of emerging collaborative forces include Kelly, D (degree centrality: NA-NA-328-29) and Tang, R (closeness centrality: NA-NA-350-24; betweenness centrality: NA-NA-123-17). We can expect that these authors will play a more important role in this field in the coming years. Table 7 summarizes the different career paths of the authors mentioned above.

Table 8 lists the top 40 authors based on the number of citations to their publications. Corresponding centrality rankings within the top 40 are displayed in bold font.

Table 8 shows some discrepancies between the citation rankings and centrality measures. Most noticeably, the seven most cited authors have very low centrality rankings. This is due to the fact that they are computer scientists and did not publish many articles in LIS journals; however, these articles are cited quite frequently (e.g., Deerwester, S, Dumais, ST, Landauer, TK, Furnas, GW, and Harshman, R coauthored an article cited 1275 times; Salton, G, and Buckley, C coauthored two articles which have been cited 906 and 328 times). As a result, they do not have direct LIS collaborators: the closest collaborator is Fox, EA, who has two degrees of separation from them, and, accordingly, they are in the periphery of the coauthorship network. Some less obvious instances include Ingwersen, P, Jansen, BJ, Marchionini, G, and so on. Although their centrality rankings correspond to their citation rankings, only a portion of their publications are incorporated in our dataset, and therefore their ranking results may be affected.

Discrepancies also exist within different centrality measures. For example, Glanzel, W has high degree centrality, indicating that he has collaborated with many authors (20 authors), but his closeness centrality is low, only ranking 384 out of 2197. The reason for Glanzel's high degree of centrality

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TABLE 7. Different career paths of selected authors.

	Plateau		On the rise		On the decline		A new force	
Closeness	Willett, P	1-1-5-2	Spink, A	224-43-1-1	Wood, EF	2-3-28-28	Tang, R	NA-NA-350-24
			Ellis, D	2054-5-2-3	Cringean, JK	4-7-51-37	Thelwall, M	NA-NA-576-13
			Saracevic, T	170-18-10-6				
			Losee, RM	313-11-4-10				
Betweenness	Willett, P	1-3-5-1	Saracevic, T	47-6-17-12	Wood, EF	3-14-54-168	Tang, R	NA-NA-123-17
	Borgman, CL	12-9-3-18			Lunin, LF	2-13-137-890	Thelwall, M	NA-NA-81-11
	Rousseau, R	8-5-13-6						
Degree	Willett, P	1-1-2-2	Spink, A	797-105-5-4	Rada, R	2-4-9-1198	Kelly, D	NA-NA-328-29
	Rousseau, R	3-2-1-1	Cronin, B	62-10-11-12	Wood, EF	6-12-26-69	Thelwall, M	NA-NA-266-10
	Lancaster, FW	4-3-6-8	Moed, HF	175-15-12-13				
			Fox, EA	410-14-30-15				
PageRank	Willett, P	1-1-2-3	Oppenheim, C	NA-12-3-1	Rada, R	5-4-11-1850	Thelwall, M	NA-NA-513-16
	Rousseau, R	3-3-1-2	Leydesdorff, L	58-28-22-6	Wood, EF	4-11-26-40		
	Lancaster, FW	2-2-4-8	Morris, A	44-21-14-13				

TABLE 8. Top 40 authors based on citation counts.

	Citation		Centrality ranking			
Author	Counts	Ranking	Closeness	Betweenness	Degree	PageRank
Salton, G	1464	1	1199	259	216	229
Buckley, C	1389	2	1200	260	216	230
Dumais, ST	1323	3	1545	172	107	106
Landauer, TK	1295	4	1844	382	292	269
Harshman, R	1275	5	1845	672	554	667
Deerwester, S	1275	5	1845	672	554	667
Furnas, GW	1275	5	1845	672	554	667
Spink, A	1253	8	**1**	**2**	**4**	**4**
Saracevic, T	1141	9	**6**	**12**	47	84
Glanzel, W	969	10	384	**34**	**18**	**27**
Thelwall, M	884	11	**13**	**11**	**10**	**16**
McCain, KW	835	12	1432	136	107	103
Ingwersen, P	791	13	41	74	76	52
Jansen, BJ	787	14	**23**	189	62	67
Egghe, L	747	15	206	147	107	79
Rousseau, R	705	16	**14**	**6**	**1**	**2**
Braun, T	704	17	897	175	47	56
Schubert, A	701	18	898	176	47	54
Borgman, CL	685	19	109	**18**	**7**	**11**
Ellis, D	654	20	**3**	**10**	**31**	**33**
Moed, HF	639	21	394	63	**13**	**20**
Kantor, P	635	22	**20**	**15**	**11**	**36**
Willett, P	609	23	**2**	**1**	**2**	**3**
White, HD	608	24	976	115	414	330
van Raan, AFJ	590	25	728	284	62	85
Cronin, B	564	26	353	**36**	**12**	**7**
Harter, SP	526	27	1041	181	136	58
Leydesdorff, L	489	28	**21**	**13**	**6**	**6**
Fidel, R	426	29	666	117	47	83
Wilson, TD	414	30	**5**	44	136	162
Ford, N	378	31	**4**	**40**	**5**	**9**
Vakkari, P	361	32	**26**	**22**	47	**37**
Jarvelin, K	350	33	**12**	**28**	**9**	**5**
Marchionini, G	346	34	358	41	**38**	**35**
Wolfram, D	320	35	**8**	**21**	47	**32**
Oppenheim, C	295	36	1969	59	**3**	**1**
Large, A	291	37	427	270	41	59
Persson, O	285	38	402	107	88	98
Losee, RM	282	39	**10**	**26**	414	346
Kling, R	274	40	1262	129	41	**23**

TABLE 9. Spearman's correlations between centrality measures and citation counts.

	Citations	Closeness	Betweenness	Degree	PageRank
Citations	1	0.2433*	0.5332*	0.3929*	0.4067*
Closeness	0.2433*	1	0.1942*	0.2013*	0.1114*
Betweenness	0.5332*	0.1942*	1	0.6557*	0.7314*
Degree	0.3929*	0.2013*	0.6557*	1	0.9503*
PageRank	0.4067*	0.1114*	0.7314*	0.9503*	1

*Correlation is significant at the 0.01 level.

but low degree of centrality is that most of his collaborators are located in Europe—mainly Hungary, Germany, and the Netherlands. Thus, he is in close proximity to European authors but is distant from authors in other regions. As a result, his closeness centrality is low. McCain, KW has high citation ranking but low centrality rankings. This is because she only collaborates with 10 authors, and all of her collaborators are located in the United States; thus, she does not have high centrality values. The same reasoning can be applied to Ingwersen and Egghe: most of Ingwersen's collaborators are located in Denmark, and most of Egghe's collaborators are located in Belgium. By comparison, the majority of Rousseau's collaborators are located in Belgium, yet he also collaborates with authors from China, Japan, India, England, and Canada, thus shortening his virtual distance from authors in the network.

In the interest of gaining a more general perspective on collaboration patterns in this LIS coauthorship network, we calculate Spearman's correlations between centrality measures and citation counts for all authors in the largest component (2,197 authors), as shown in Table 9.

Table 9 illustrates that four centrality measures have significant correlation with citation at the 0.01 level, with betweenness having the highest. Closeness centrality has the lowest correlation with citation and other centrality measures, which may be the result of its distinct distribution pattern (Figure 2) from the other three measures. It is also worth noting that PageRank and degree centrality are highly correlated ($R = 0.9503$), which is the result of their similar distributions. Litvak, Scheinhardt, & Volkovich (2008) also found that distributions of PageRank and degree differ only by a multiplicative constant. Fortunato, Boguñá, Flammini, & Menczer (2008) argued that PageRank can be approximated by degree, a local measure which is more accessible.

The correlation of citation counts with centrality suggests that, to a certain degree, centrality measures also assess an author's scientific productivity and impact. They can be indicators of impact evaluation, at least supplementary indicators for impact evaluation, providing alternative perspectives for current methods. Meanwhile, Ma, Guan, & Zhao (2008) found that for paper citation networks, citation has significant correlation ($R = 0.9$) with PageRank. Compared to this figure, the correlation for the LIS coauthorship network is low. One of the main factors contributing to this difference is the type of network under study. Ties for the paper citation network are citation relations. Compared to the coauthorship network, whose ties are coauthor relations, paper citation networks are more pertinent to citations, and, thus, it is reasonable for paper citation networks to have higher correlations with citation counts.

Figure 3 shows the scatterplot between citation rankings and centrality rankings. For the top-ranked nodes, their citation rankings and centrality rankings have certain correlations. For lower-ranked dots, each citation rank has a wide range of centrality ranks rather than a single rank, and consequently their centrality rankings and citation rankings do not have correlations. The result indicates that centrality in the tail part are inconsistent, meaning that they are very susceptible to fluctuations: a little higher or lower for citation rankings would result in a significant change for centrality rankings. Such fluctuations result in a low correlation between citation rankings and centrality rankings.

Discussion and Conclusion

The evolving coauthorship network effectively reveals the dynamic collaboration patterns of authors. The different positions of authors during different time periods reflect their collaboration trends. We find that some authors are ranked highly in each time period, indicating that they are on the "plateau" of their academic career; furthermore, some authors are on the rise in this field while others are on the decline because they are retiring or switching their research focuses to other fields.

We also verify the correlation between citation and centrality. We find that all four centrality measures are significantly correlated with citation counts; nevertheless, some inconsistencies occur. These can be interpreted from two perspectives. First, citations and centralities measure different content. Although the motivation for citation varies, citation counts measure the impact of articles (Garfield & Sher, 1963; Frost, 1979; Lawani & Bayer, 1983; Baird & Oppenheim, 1994). Centrality measures, on the other hand, quantify an author's impact on the field which is, in effect, the counterpart of article impact, as illustrated in Figure 4.

As per this model, social capital stands for the value of scientific collaboration. Betweenness in terms of structural holes is also a form of social capital. Betweenness reflects how close the subnetwork to which the author belongs is and how important the author's role as a brokerage is. Thus, betweenness creates advantage by lowering the risk of collaboration and by increasing the value of collaboration (Burt, 2002). Authors with high betweenness centrality have more opportunities to broker the flow of information and, thus, they have a higher social capital (Burt, 2002). Besides, degree centrality measures both strong ties and weak ties of authors; closeness centrality measures authors' positions and their virtual distance from others in the field; PageRank measures authors' impacts via their collaborators. Thus, degree centrality, closeness centrality, and PageRank also measure authors' impacts on the field and their social capital. Article impact can be quantified by citation counts; similarly, author impact on the field can also be quantified through centrality measures.

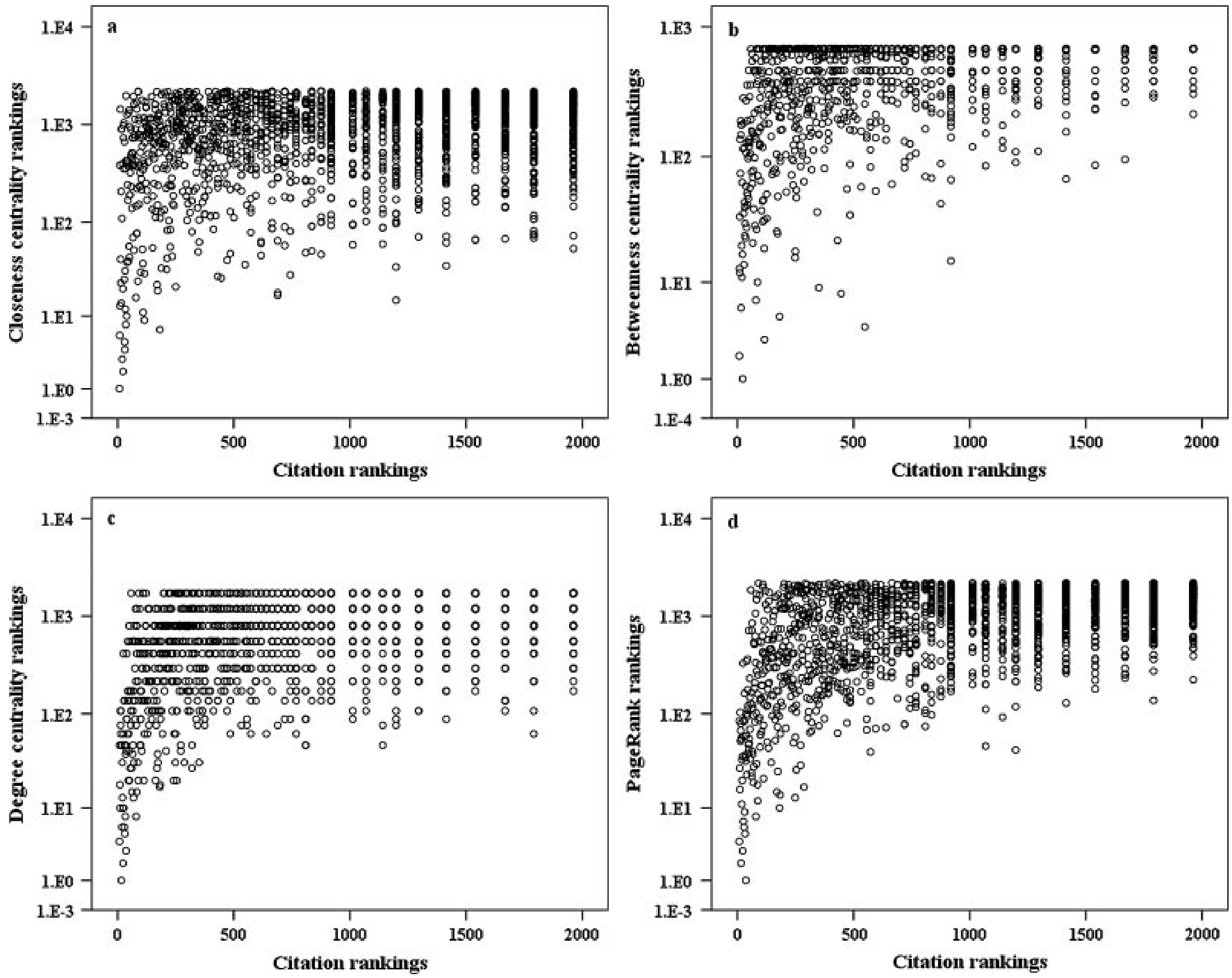

FIG. 3. Scatterplot between citation and closeness (a), betweenness (b), degree (c), and PageRank (d).

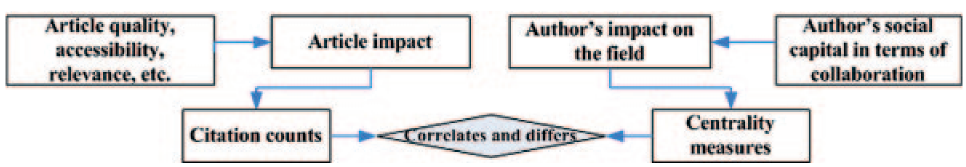

FIG. 4. Relation between citation and centrality.

Accordingly, citation is a metric of article impact, and centrality is a metric of author impact, so it is not surprising to find that they are correlated but also differ in their representation.

The limitations inherent to the current algorithm of centrality measures are another factor contributing to these discrepancies. Authors coauthoring with multiple authors have high degree centrality. For instance, if a paper is coauthored by 10 authors, each of these authors would have a degree centrality of 9. This is equivalent to 45 papers if they were coauthored by just two authors—obviously quite different academic impacts. Closeness centrality is a measure of network property rather than a direct measure of academic impact. Any author coauthoring an article with authors having high closeness centrality would also result in a high closeness centrality; however, this author may have little academic impact. Authors involved in interdisciplinary research would have a high betweenness centrality even though their role in the specific discipline of LIS may not be that significant. Centrality measures, therefore, will be much more useful and valuable if these drawbacks could be eliminated.

In fact, some scholars already attempt to minimize these drawbacks. Newman (2005) proposed a new betweenness measure that includes contributions from essentially all paths between nodes, not just the shortest, meanwhile giving more weight to short paths. Brandes (2008) introduced variants of betweenness measures, as endpoint betweenness, proxies betweenness, and bounded distance betweenness. Liu et al. (2005) defined AuthorRank, a modification of PageRank, which considers link weight. Other work aimed at improving PageRank in the context of author ranking includes Sidiropoulos & Manolopoulos (2005) & Fiala, Rousselot, and Ježek (2008). In future studies it will be necessary to improve the algorithm of centrality measures and utilize their strengths in improving current impact evaluation. Potentially, it also may prove necessary to apply centrality measures to other social networks (e.g., co-citation networks).

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