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Co-authorship Network Analysis of iMetrics Researchers

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Abstract

Using a combination of bibliometrics and social network analysis methods, co-authorship network of iMetrics was studied in the time spam of 1978-2014 and top researches in the field were identified. Then, the relationship between these researchers' productivity, performance, and centrality indicators was investigated. Out of 5944 studied records, researchers such as Leydesdorff L, Glanzel W and Rousseau R gained the higher centrality measures. There was a significant relationship between productivity and performance. Based on multivariate regression analysis, there was a significant relationship between degree centrality and betweenness centrality on one hand and productivity on the other hand. Centrality measures explained 58% of variance of performance.

Keywords: Co-authorship, collaberation, centrality, Productivity, Performance.

Introduction

Nowadays, scientific collaboration is prevalent in various scientific disciplines. Scientific collaboration has been resulted from knowledge complexity, increase in demand for more specialization, and interdisciplinary skills in research. It is a social phenomenon in research and has been studied systematically since the 1960s. Since then, some increase in the rate of scientific collaboration has been reported by various researchers.

Social network analysis is used for describing the scientific collaboration patterns identified by co-authorship relations (Stefano, Giordano & Vitale, 2011). Scientists included in the collaboration networks share their ideas, use similar methods and techniques for extracting and analyzing research data and influence each other's works. As one of the most documented and tangible forms of scientific collaboration and the most formal manifestation of intellectual share among authors in producing scientific works, co-authorship is the collaboration among two or more authors on producing a work that results in a production with

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higher quality and quantity than that produced by a single author (Hudson, 1996). Collections of such collaborations among researchers can construct a co-authorship network in which authors form nodes and the line between two nodes is considered as the co-authorship relation created in the papers. As a main category of social networks, the co-authorship network can be used for determining the structure of scientific collaboration and individual authors' research states (Liu et al., 2005).

On the other hand, one of the complex debates in bibliometrics is researchers' scientific influences. Since some authors relate a researcher's scientific influence to the citation rate of his/her works, scientific influence is not restricted to one's works and a researcher's interaction with other researchers in a field is at work when considering his/her scientific influence, i.e. his/her social influence. Social influence is one's ability to influence others by a means of social interaction processes (Truex et al. 2011). In other words, the expansion of a researcher's thoughts can be measured by studying his/her co-authorship trends in a certain scientific field (Cuellar et al. 2016). Three measures of centrality (degree, betwenness, and closeness) are often used for measuring the social influence. Centrality is one of the most important and common measures in analyzing social networks, especially for identifying main and powerful influencing actors.

Considering the above-mentioned points, this study aims at investigating the relationship between researchers' productivity and performance with their centrality measures among researchers in the iMetrics. Specifically, this study attempted to determine:

1. The rankings of iMetrics researchers based on their centrality (including degree, betweenness, and closeness) measures;
2. The possible relationship between productivity (the number of articles) and centrality measures; and
3. The possible relationship between performance (the number of citations) and centrality measures.

Literature review

Several scholars have directly applied centrality measures to co-authorship networks in different fields (Barabasi et al. 2002; Otte & Rousseau, 2002; Mutschke, 2003; Liu et al, 2005, Acedo et al, 2006; Krichel & Bakkalbasi, 2006; Liu et al, 2007; Hou et al, 2008; Gómez et al, 2008). On the other hand, the study of research productivity, citation impact and collaboration has a long-standing tradition in LIS research, and these three indicators have been employed in many disciplines to measure research success in terms of output (Abrizah et al. 2014). To be more specific, the relationship between social network structures in co-authorship network and research productivity and impact is studied in several studies (Newman, 2001; Egghe et al. 2007; Abbasi and Jaafari 2013; Yin et al. 2006).

Among them, Hou, Kretschmer and Liu (2008) investigated the structure of scientific collaboration networks in scientometrics at the level of individuals by using bibliographic data of all papers published in the international journal Scientometrics during 1978–2004. The result showed that Glanzel is the central author of the whole network in terms of the highest degree, betweenness and closeness centralities, which indicates that he is the most influential person in the network. With respect to sub-networks. Moreover, they found a positive and significant correlation between output of authors and the centrality measures, which revealed that most of the prolific authors were also active in collaboration network in the field of scientometrics.

Yan and Ding (2009) indicated that co-authorship centrality measures are significantly associated with citation counts, with betweenness centrality having the strongest association. Badar et al. (2012) examined the association of co-authorship network centrality (degree, closeness and betweenness) and the academic research performance of chemistry researchers in Pakistan. Results related to regression revealed a positive impact of degree and closeness and negative impact of betweenness centrality on research performance. Temporal analysis using node-level regression confirmed the direction of causality and demonstrated a positive association of degree and closeness centrality on research performance.
Guns et al. (2010) found that top authors in Scientometrics and Journal of Informetrics had the highest global collaboration network centrality measures. Moreover, Liao and Yen (2012) indicated that the degree of research collaboration had a strong positive relationship with research productivity.
In a more recent study, Abrizah et al. (2014) investigated the field of informetrics to identify publication strategies that have been important for its successful researchers. They used a micro-analysis of informetrics researchers from 5,417 informetrics papers published in 7 core informetrics journals during 1948–2012. Findings revealed that the 30 most productive informetrics researchers of all time span several generations and seem to be usually the primary authors of their research, highly collaborative, affiliated with one institution at a time, and often affiliated with a few core European centres. Their research usually has a high total citation impact but not the highest citation impact per paper. Moreover, results indicated that the most cited authors also tend to be the most productive authors: 20 of the 30 most cited authors are also in the most productive 30. Based on

betweenness centrality, Glanzel, Rosseau, and Leydesdorff gained the highest scores, respectively.

Results of Soheili, khademi and mansouri (2015) showed that there is a significant correlation between Journal Impact Factor (JIF) and all centrality measures except closeness centrality at P= 0.001. Results also showed that there is a significant correlation between productivity of authors and all centrality measures scores at P≥ 0.001. Also, regression reports direct relationship of degree, closeness and flow betweenness and inverse relationship of betweenness as well as Eigen vector centrality on productivity of researchers.

Methodology

This research applied co-authorship analysis and social networking analysis. The research population consisted of the iMetric papers that were indexed in the Web of Science (WoS) during 1978-2014. It worth nothing that in research on fields such as bibliometrics, informetrics, webometrics and in general, iMetrics, the lack of a justified and appropriate statistical population can be seen. However, the selection of primary data is important in every iMetrics study as it directly affects consequent results and findings. Therefore, it is better to include comprehensive primary data. Considering this main point, following the methodology innovated by Milejeciv and Leydesdorff (2013), the statistical population of this research included all papers published in *Scientometrics* and the *Journal of Informetrics*, as well as iMetrics papers published in the six journals including the *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*. The reason for selecting these journals was that they published most papers in the field of iMetrics (Milejeciv and Leydesdorff, 2013). In addition, the journal *Scientometrics* is the first specialized journal in iMetrics field that has been published since 1987 and developed the field (Milejeciv and Leydesdorff, 2013; Leydesdorff, et al., 2014). Therefore, the time spam of 1978-2014 was selected for this research.

Data collection

A relatively comprehensive method was used for data collection. This method introduced by Milejeciv and Leydesdorff (2013). At first, all scientific productions in the WoS that were published in the eight above-mentioned journals were extracted. Then, documents labeled under “article” or “proceeding” were selected. The papers irrelevant to iMetrics field in the six journals including *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* were excluded. All papers published in *Scientometrics* and the *Journal of Informetrics* were included, however. The preposition of exclusion was that 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 papers published in the *Scientometrics* or the *Journal of Informetrics* were included. In other words, citation to papers published in *Scientometrics* and the *Journal of Informetrics* as main journals of iMetrics field was the criterion for separating the papers published in the other six journals in iMetrics field from those of non-iMetrics field. The software isi.exe was used for records screening.

Many related papers were retrieved by applying this method. However, it was probable that some related papers published in these journals had no citation to *Scientometrics* or the *Journal of Informetrics*. For retrieving such papers, some commonly-used and highly-frequent keywords in the field extracted from previous researches were used in the following search strategy that resulted in some other related items:

> 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 to achieve a complete statistical population, 5944 papers in iMetrics field were identified and analyzed. As shown in Table 1, most of these papers were published in the journals of *Scientometrics*, *JASIST* and *Informetrics*, respectively.

Table 1. Distribution of iMetrics papers published in the studied journals

Journal name	No. of papers	No. of articles	No. of iMetrics articles (after applying citation and keyword filters)	
			Keyword filters	Citation filters
Scientometrics	4003	3556	3556	
JASIST	5194	3503	758	87
Journal of Informetrics	510	463	463	
Research Policy	2680	2248	327	26
Research Evaluation	429	384	213	18

Journal of Information Science	1941	1434	146	28
Information Processing and Management	2965	1968	145	43
Journal of Documentation	2714	866	91	43
Total	20436	14422	5944	

Data Analysis

First, all the authors of the documents were extracted. The authors were then edited and modified and those authors whose name were written in several ways changed to the preferred name. In order to show the main structure of the network, each author must published 4 papers or more to be included in this study. This threshold resulted in a total of 626 prolific authors publishing 4 or more papers during 1978 to 2014, among them there are 609 authors published co-authorship papers, accounting for 97.28% of the prolific authors. It is necessary to mention that some authors such as Vinkler (34 papers), Sangwal (11 papers), Haitun (10 papers), and Kosmulski (10 papers) have published no co-authored paper. In the next step of the co-authorship square matrix consisting of 609 researchers was created and imported to the UCINet. Using UCINet, the matrix was converted into a correlation matrix, centrality indicators were calculated by UCINet, and the network visualized using NetDraw.

Results

In total, 13,258 authors' frequency were involved in authoring 5,944 papers in the iMetrics that represented 2.23 authors per paper. The number of unique author names in the studied sample was 5,476. The rate of productivity based on the number of published papers revealed that "Leydesdorff L" with 146 papers and "Rousseau R" with 136 papers were in the first and second ranks, respectively. "Egghe L" and "Glanzel W", each with 134 papers were in the next rank and "Thelwall M" with 113 papers was in the fifth rank. As table 2 shows, the difference in the number of papers produced by these five authors is much more than that of other authors. It is worth noting that these authors may have other papers in the fields other that the iMetrics that are not included in this study, however.

Rank	Author Name	#Papers	Rank	Author Name	#Papers
1	**Leydesdorff L**	146	16	**Tijssen RJW**	39
2	**Rousseau R**	136	17	**Ding Y**	35
3	**Glanzel W**	134	18	**Lewison G**	35
4	**Egghe L**	134	19	**Chen DZ**	34
5	**Thelwall M**	113	20	**Guan JC**	34
6	**Bornmann L**	83	21	**Vinkler P**	34
7	**Schubert A**	81	22	**Burrell QL**	33
8	**VanRaan AFJ**	76	23	**Cronin B**	33
9	**Moed HF**	62	24	**Gupta BM**	33
10	**Braun T**	60	25	**Bar-Ilan J**	31
11	**VanLeeuwen TN**	58	26	**Bordons M**	31
12	**Abramo G**	50	27	**Waltman L**	31
13	**D'Angelo CA**	50	28	**Lariviere V**	30
14	**Daniel HD**	44	29	**Kretschmer H**	29
15	**Huang MH**	44	30	**Small H**	29

Table 2. 30 highly-productive authors in the iMetrics

The primary analysis of records by Publish or Perish Software revealed that out of 5,944 papers, 2,048 papers (34.46%) were authored by one author, as a prevalent authorship pattern in iMetrics and the remainding papers (65.54%) were authored by two or more authors, as the co-authorship pattern. As shown in table 3, 2-author pattern with 1911 papers, 3-author pattern with 1911 papers and 4-author pattern with 487 papers were in the second to fourth ranks, respectively. Only one paper was authored by 11, 15, 23 or 26 authors in the field.

Table 3. The frequency of authorship patterns in iMetrics research

Rank	Authorship Pattern	Frequency	%
1	1-author	2048	34.45
2	2-author	1911	32.15
3	3-author	1170	19.68
4	4-author	487	8.19
5	5-author	203	3.42
6	6-author	62	1.05
7	7-author	26	0.44
8	8-author	16	0.27
9	9-author	12	0.2
10	10-author	5	0.08
11	Other	4	0.07
Total		5944	100

Top iMetrics researchers based on three centrality measures

The iMetrics researchers' ranking is shown in table 4 based on three centrality measures (including degree, betweenness, and closeness centralities). The highest degree centrality belonged to "Glanzel W". "Rousseau R" and "Thelwall M" were in the second and third ranks, respectively. Considering the rate of betweenness centrality, "Leydesdorff L", "Rousseau R" and "Glanzel W" were in the first, second and third ranks, respectively. As table 4 shows, the highest closeness centrality measures belonged to "Leydesdorff L", "Rousseau R" and "Rafols I", respectively. Researchers appearing in all columns are highlighted in bold and those in two of the columns are shown in underline.

Table 4. iMetrics researchers' ranking based on the centrality measures

Ranking by betweenness centrality			**Ranking by closeness centrality**			**Ranking by Degree centrality**		
Rank	Researcher's Name	Betweenness centrality	Rank	Researcher's Name	Closeness centrality	Rank	Researcher's Name	Degree centrality
1	**Leydesdorff**	1166792	1	**Leydesdorff**	0.085788	1	**Glanzel**	215
2	**Rousseau**	837081	2	**Rousseau**	0.085273	2	**Rousseau**	179
3	**Glanzel**	409985	3	Rafols	0.0846535	3	**Thelwall**	159
4	Ye FY	329995	4	**Glanzel**	0.0846444	4	**Leydesdorff**	158
5	Zitt	259213	5	Ye FY	0.084483	5	**Bornmann**	133
6	**Chen CM**	246140	6	Kretschmer	0.084345	6	SCHUBERT	125
7	**Thelwall**	240091	7	Egghe	0.084326	7	**vanLeeuwen**	123
8	Rafols I	222711	8	Meyer	0.084267	8	Van Raan	121
9	Park HW	219092	9	**Bornmann**	0.084259	9	Huang	116
10	Kretschmer	197871	10	**deMoya-Anegon**	0.084217	10	**Moed HF**	110
11	Chen DZ	189957	11	Liang	0.084067	11	**Chen CM**	109
12	Aguillo	181172	12	Persson	0.084062	12	Braun	102
13	Zhu DH	180924	13	Jin	0.083929	13	Abramo	95
14	Ding Y	179148	14	Zuccala	0.08389	14	D'Angelo	95
15	Lepori B	174288	15	Zhou	0.083803	15	Daniel	80
16	**Porter AL**	170769	16	Wouters P	0.08376	16	Ding Y	79
17	**Zhang J**	160646	17	Van den Besselaar	0.083751	17	**deMoya-Anegon**	78
18	**Moed HF**	154330	18	Aguillo IF	0.083737	18	Debackere K	76
19	**deMoya-Anegon**	147512	19	**Chen CM**	0.083679	19	Gomez I	68

20	Liang LM	140705	20	**Thelwall M**	0.08362	20	Lariviere V	66
21	Li J	136029	21	**Moed HF**	0.083562	21	Bordons M	62
22	Zuccala A	130648	22	Cronin B	0.083524	22	Lepori B	62
23	**vanLeeuwen**	129590	23	Milojevic S	0.083486	23	Waltman L	61
24	Okubo Y	129311	24	**Porter AL**	0.083480	24	**Porter AL**	60
25	Probst C	119397	25	Thijs B	0.083404	25	van Eck NJ	59
26	Su XN	119215	26	Park HW	0.083382	26	Thijs B	58
2	Oppenheim C	118055	2	**vanLeeuwen**	0.083374	2	**Zhang J**	57
28	Meyer M	116494	28	Debackere K	0.083332	28	Egghe	53
29	ZHU J	113275	29	Guerrerobote VP	0.083312	29	Sugimoto CR	53
30	**Bornmann**	112952	30	**Zhang J**	0.083299	30	Visser MS	49

The relationship between productivity and centrality measures

Regression analysis was used for exploring the possible relationship between authors' productivity and centrality measures. The results of analysis of variance (ANOVA) for regression analysis are depicted in table 5.

Table 5. ANOVA for regression analysis of productivity and centrality measures

Variation source	Sum of squares	df	Mean square	F	p	R	^{2}R	SE
Regression	461.96	3	487.32	591.515	p≤ .01*	0.86	0.74	7.364
Residual	493.33	622	224.54					
Total	954.01	625						

Based on the results of regression analysis (F= 591.517, p≤.01), the centrality measures explain 74% of variance of productivity (R^2= .74). Considering the significant effect of productivity on the centrality measures, the coefficients of prediction equation was shown in table 6.

Table 6. The coefficients of prediction equation in the model of effect of the centrality indicators on productivity

Model	Co-efficient	Std Error	Beta (Standardized coefficients)	t	P
Constant	7.198	1.371		5.244	p≤ .01*

Betweenn s	0.0000512	0.000	0.256	9.463	p≤ .01*
Degree	0.447	0.018	0.692	25.242	p≤ .01*
closeness	-82.406	18.948	-0.092	-4.349	p≤ .01*

The regression coefficients of each predicting variable showed that each centrality measure can significantly explain the variance of productivity variable ($p \leq 0.01$). The effect coefficient of degree centrality showed that 1 unit increase in degree centrality can increase 0.692 rate in productivity (B= 0.692, $p \leq 0.01$). The effect coefficient of betweenness centrality showed that 1 unit increase in betweenness centrality can increase 0.256 rate in productivity (B= 0.256, $p \leq 0.01$). However, the effect coefficient of closeness centrality showed that 1 unit increase in closeness centrality can decrease 0.092 rate in productivity (B= - 0.092, $p \leq 0.01$).

The relationship between performance and centrality measures

Regression analysis was used for exploring the possible relationship between performance and centrality measures. The results of ANOVA for regression analysis are depicted in table 7.

Table 7. ANOVA for regression analysis of performance and centrality measures

Variation source	Sum of squares	df	Mean square	F	p	R	R^2	SE
Regression	57800000	3	487.32	288.628	p≤ .01*	0.763	0.582	258.35
Residual	41520000	622	224.54					
Total	99320000	625						

Based on the results of regression analysis (F= 288.628, $p \leq 0.01$), the centrality measures explain 58% of variance of performance (R^2= 0.582). Considering the significant effect of performance on the centrality measures, the coefficients of prediction equation was shown in table 8.

Table 8. The coefficients of prediction equation in the model of effect of centrality indicators on performance

Model	Co-efficient	Std Error	Beta (Standardized coefficients)	t	P

Constant	56.60	48.097		1.177	p≤ .01*
Betweennes	0.002	0.000	0.272	7.934	p≤ .01*
Degree	10.16	0.621	0.569	16.357	p≤ .01*
closeness	1251.251	664.79	0.051	1.882	0.06

The regression coefficients of each of these predicting variables showed that two centrality indicators (degree and betweenness) can significantly explain the variance of performance as the dependent variable ($p \leq 0.01$). The effect coefficient of degree centrality showed that 1 unit increase in degree centrality can increase 0.569 rate in performance ($B= 0.569$, $p \leq 0.01$). The effect coefficient of betweenness centrality showed that 1 unit increase in betweenness centrality can increase 0.272 rate in productivity ($B= 0.272$, $p \leq .01$).

Discussion

Recently, various researchers applied the centrality as a measure for analyzing co-authorship networks (Mutschke, 2003; Yin et al. 2006; Liu et al. 2007). These researchers believe that the centrality is an effective indicator of scientific influence. In this study, the iMetrics researchers' co-authorship network was studied based on common centrality measures. The possible relationship between productivity and performance on one hand and centrality measures on the other hand were investigated, as well.

The findings showed that the average number of authors per paper was 2.23. In a similar vein, Egghe (2012) found that the average number of authors per paper in the *Journal of Informetrics* was 2.28. The one-author pattern (with 34.46%) was the most common approach to authoring in iMetrics. For example, as a famous top researcher, Vinkler is a researcher in the field who inclusively published his works under the one-author pattern. Two-author and three-author patterns were in subsequent ranks. A paper published in the *Research Policy* in 2011 entitled "The European university landscape: A micro characterization based on evidence from the Aquameth project" owned the highest number of authors (26 authors).

The results related to co-authorship centrality measures revealed that researchers such as "Glanzel", "Rousseau", "Leydosdorff", "Thelwall" and "Bornmann" were five top authors based on degree centrality. Such researchers with higher degree centrality have more opportunities and alternatives in comparison with others. This findings is largely in accordance with that of Erfanmanesh et al. (2012). Including the papers published in the *Scientometrics*, they found “Glanzel”, “Schubert”, “Rousseau”, “Braun” and “Debackere” as top researchers based on degree centrality in scientometric studies.

Based on betweenness centrality measure, “Leydesdorff”, “Rousseau”, “Glanzel”, “Ye” and “Zitt” were five top researchers. The high betweenness centrality gives the actor an opportunity to mediate the contacts among other actors. The actors who access other actors with a shortest path or ones accessible in a short path by other actors have appropriate position in the network. This structural advantage could be interpreted as “power” and ones with such posiotions in the network are more powerful researchers than others. In a research by Erfanmanesh et al. (2012), the higher betweenness centrality belonged to “Glanzel”, “Rousseau”, “Leydesdorff”, “Meyer” and “Zitt”, respectively. Moreover, Abrizrah et al. (2014) found “Glanzel”, “Rousseau”, “Leydesdorff”, “Kretschmer” and “Liang” as authors with higher betweenness centrality, respectively.

Regarding the closeness centrality, “Leydesdorff”, “Rousseau”, “Glanzel”, “Rafols” and “Ye” were among five top researchers. There are more connection between these authors and others and their connections are made with few mediators. As a result, the distribution and dissemination of information is speedy among them. Of these top researchers, “Rousseau” and “Glanzel” are among the five top researchers in the study by Erfanmanesh et al. (2012). They found “Glanzel”, “Rousseau, “Meyer”, “Debackere” and “Kretschmer” as five top researchers, respectively. The difference may be due to the sample studied in their research, i.e. the papers published in the *Scientometrics.*

After identifying prolific and highly-cited authors in iMetrics, regression analysis showed a significant relationship between productivity and performance. Therefore, it can be concluded that iMetrics researchers considered both quantity (the number of papers) as well as quality (the number of citations). In other words, the more the paper published by the researchers in the field of iMetrics, the more the citation their papers received. This finding is in line with that of Rumsey-Wairepo (2006) that found positive relation between productivity and performance. However, this finding is not accorded with that of Abrizah et al. (2014) that found that highly-productive authors are not necessarily highly-cited ones.

After measuring the indicators involved in social influence (degree, betweenness and closeness centralities), the relationship between these indicators (as independent variables) and the authors’ productivity as well as performance (as a dependent variables) was investigated by applying a multivariate regression analysis. The results showed that there was a significantly positive relationship between degree centrality and betweenness centrality (as independent variables) on one hand and performance (as the dependent variable) on the other hand. This was so in the case of all three indicators (as independent variables) and productivity (as a dependent variable). Such relationships have been found in other studies, such as Glanzel and Schubert (2001), He, Geng and Campbell-Hunt (2009). Stringer (2009) found that researchers with higher centrality in a co-authorship network have better research performance (productivity and performance).

In addition, Borgman and Furner (2002) believe that higher rates of collaboration are usually associated with higher productivity. Egghe et al. (2007) gave three explanations for this reality: (a) authors involved in co-authored papers have more time to write additional papers since part of the work is done by the other co-authors; (b) collaboration could be higher between the better researchers, which then leads to higher production; and (c) collaboration is higher in fields with highly productive large research laboratories.

The relationship between co-authorship centralities and citation performance showed that higher centrality in the network results in higher citation absorption capacity. Yang and Ding (2009) and Li, Liao and Yen (2013) found that the more the betweenness centrality is, the more the citations an author receives. In a co-authorship network, the researcher with higher closeness centrality has speedy access to all researchers in the network and receives needed resources as soon and appropriate as possible. Appropriate access to resources can result in an increase in the quality of publications. As the high quality of publications can increase the number of received citations, it can be concluded that in a co-authorship network, researchers who are closer to other researchers (who have higher closeness centrality) can receive more citations.

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