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Correlation between Impact Factor and productivity with centrality measures in journals of Information science: A social network analysis

Faramarz Soheili
Payame Noor University, Tehran, Iran
Corresponding author: fsohieli@gmail.com

Rohallah Khademi
Shahid Chamran University, Ahvaz, Iran

Ali Mansoori
Isfahan University, Isfahan, Iran

Abstract

This research examines the association between co-authorship network centrality (degree, closeness, betweenness, eigenvector, Bonacich flow betweenness) and productivity of Information science researchers. The research population includes all those researchers who have published at least one record in one of the twenty journals of Information Science which has an impact factor of 0.635 as a minimum from the years 1996 to 2010. By using social network analyses, this study examines information science researchers' outputs during 1996-2011 in ISI Web of Science database. In general co-authorship network of these researchers was analyzed by UCINET6 software. Results 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.

Keywords: Co-authorship; Network centrality; Scientific productivity; Social network analysis, Journal Impact Factor

Introduction

The increasing cooperation in science, which has led to larger co-authorship networks, requires the application of new methods of analysis of social networks in bibliographic co-authorship networks as well as in networks visible on the Web (Kretschmer, 2004). Social network is a network of relationship which is made as a result of cooperation between scientists, organizations, countries, and others in common (similar) or different majors and their interrelationships. A social network is basically a set of actors and relationships that interweaves these actors together. Actors can be persons or aggregated parts such as groups, organizations or their families. Actors form social networks by exchanging many sources with each other. Such resources can be information, goods, and services, social or financial support. This type of resource exchange is considered as social network relationship. Whenever individuals make relationship, it is believed that a node is created (Emirbayer, 1997). Strength of nodes between individuals may vary from weak to strong and depends on the number and the types of sources, abundance and intimacy of exchanges (Marsden & Campbell, 1984).

Networks which are formed according to cooperation are reviewed and analyzed on the basis of different measures, one of the most important of which is "centrality measure". "Centrality is one of the oldest concepts in network analysis. Most social networks contain people or organizations that are central. Because of their position, they have better access to information, and better opportunity to spread information. This is known as the ego-centric approach to centrality. The network is centralized from socio-centric perspective. The notion of centrality refers to the positions of individual vertices within the network, while centralization is used to characterize an entire network. A network is highly centralized if there is a clear boundary between the center and the periphery. In a highly centralized network, information spreads easily, but the center is indispensable for the transmission of information" (Said, et al, 2008). "The status of an actor is usually expressed in terms of its centrality, i.e., a measure of how central the actor is to the network graph. Central actors are well-connected to other actors and metrics of centrality will therefore attempt to measure an actor's degree (number of in- and out-links), average distance to all other actors, or the degree to which geodesic paths between any pair of actors passes through the actor" (Liu et al, 2005).The simplest measure of centrality is the number of links that a member of a network has with other network members. Indeed, person's centrality represents his/her prestige and authority in the network. Those who are located in the center of network have more academic influence.

In the subject of Social Network Analysis, ranking the individuals in social networks, namely the analysis of individuals' importance or centrality is an important and core task (Chakrabarti & Faloutsos, 2006).Therefore, analyzing the central or important authors in the co-author networks should be associated with their importance and validity. In addition, analysis of important authors can help researchers assess the educational departments. "In academic research, it is exceedingly rare that a researcher produces outcomes with no connection to the context of the research community. New findings are usually derived from the context of research community, that is, from the accumulation of preceding research or cooperative relationships in the research domain. Therefore, when we analyze the activity of the researchers in some domain for the purpose of grasping the characteristics of that domain in producing knowledge, we are obliged to not only evaluate each researcher's activity individually, but also take into consideration his/her position in the structure of some kind of intellectual tie" (Yoshikane, Nozawa & Tsuji, 2006). In this study, therefore, authors of information science have been assessed by the centrality measure. We also try to examine these hypotheses A: there is a significant correlation between co-authors centrality scores and Journal impact factor. B: there is a significant correlation between centrality scores and authors productivity among information science researchers.

Literature review

In recent years, scientific outputs of scientists have been investigated from different aspects in several studies. Some studies survey growth rate, some of them scientific collaboration, or else citation and co-citation networks, others co- authorship networks and some mapping scientific structure, etc. Recently, the characteristics of co-author networks as social networks have been highlighted (Kretschmer, 2004). In this regard, various methods and the indexes, one of which is centrality, have been used for the co-authorship assessment.

As for the individuals' centrality in social networks, Freeman's centrality measures of degree, closeness and betweenness are the most commonly used (Freeman, 1979). In the subject of social network, another classical measure of centrality is the eigenvector centrality, which is also based on the interdependence or the reinforcing effect (Bonacich, 1987). Many scholars have applied the above mentioned centrality measures to co-authorship networks. Newman studied a variety of properties of his networks, including scientists' degree and betweenness (Newman, 2001). Some studies have directly applied the degree, closeness and betweenness to co-authorship networks of different domains (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). Lu & Feng (2009) proposed centrality measurers based on the extensity of authors' collaborative relationships in co-authorship networks, i.e., the extensity centrality.

Barabasi et al (2002) analyzed the social structure of research collaborations in the context of other scientific disciplines such as physics and biology. Racherla and Hu (2010) studied the field of tourism research community. Fatt, Ujum and Ratnavelu (2010) investigated the Journal of Finance. Hill (2008) tried to investigate the relationship between social network structures in co-authorship network and research productivity. Based on the review of prior literature in social network analysis, she chose the measures of eigenvector centrality (extent of being connected to influential members of the network), betweenness centrality (extent of importance in connecting other members of the network), as well as the E-I Index (measure of dominance of external over internal ties in organizational subunits) to describe potential structures in co-authorship network. She then used publication data from tenured faculty in a computer science department in a US university and statistically tested the association between each of the measures and research productivity.

In addition to above-mentioned studies, many other articles used centrality measures for analyzing co-author networks. Their researchers have claimed that the centrality measure is useful in assessing the co-authorship impact. Badar et al (2012) examines the association of co-authorship network centrality (degree, closeness and betweenness) and the academic research performance of chemistry researchers in Pakistan. Higher centrality in the co-authorship network is hypothesized to be positively related to performance, in terms of academic publication, with gender having appositive moderating effect for female researchers. Results related to regression report positive impact of degree and closeness and negative impact of betweenness centrality on research performance. Temporal analysis using node-level regression confirms the direction of causality and demonstrates a positive association of degree and closeness centrality on research performance.

Methodology

This study is conducted on the basis of network analysis which examines various forms of relationship between documents, authors, words, citations and links between web pages, institutes and organizations forming altogether a network. This method examines the interaction between people, organizations, groups, and the like and identifies invisible patterns between these items in order to facilitate more effective cooperation between the items mentioned.

In this study, social network analysis has been used to gain a good perception of the node (namely, identifying authors with central role) in information science researchers. The origins of contemporary network analysis are in the fields of sociology, anthropology, and graph theory. It is a relatively new area (late 50's) with much activity since the mid 70's (Holland & Leinhardt, 1979; Betts & Stouder, 2004). General principle in a network approach is that at the beginning the characteristics between and within departments should be examined not the properties of units. In social and communication science, this units can be individuals, groups, organizations or communities. Furthermore, relations can include people’s feeling about each other, information exchange, money and goods exchange (Burt, 1992; Haythornthwaite, 1996).

Population of this study was all researchers who have at least one article in each of the 20 top journals in information science indexed in Thomson Reuter's database, in a 15-year period. These 20 journals are selected from 67 Journals in the field of information science with Impact Factor (IF) higher than 0.6 and 15 years’ experience in information science in publishing indexed in SCI database. The names of journals were selected from the 2011 version of JCR. At first we searched for all articles published in the given journals and then have calculated the SNA metrics first for the journals (to check their correlation with IF) and then for the authors (to check their correlation with productivity). The UCINET, version 6 and its supplementary package NetDraw were employed for data analysis. Coauth.exe was also used for preparing co-author matrix. Statistical analysis was performed using the SPSS software version 16; variables were analyzed using Pearson correlation and multiple regressions to address any relationship between centrality scores with IF and productivity.

In second phase, after identifying authors who had high centrality role in this research, the questionnaires with 3 open-ended questions were distributed to them. For selecting the sample of the study, we selected the top 10 authors with centrality role in the studied journals. Totally 356 authors received high centrality scores. Based on Cochran formula, we selected 154 authors.

Results

In this section, we analyze the data related to research hypotheses. The data extracted from the journals were 21822 records, written by 47848 authors. Various centrality measures (Degree, Closeness, Betweenness, Flow betweenness and Eigenvector) for 20 examined journals are shown in Table 1.

One of the network measures and useful indexes for analyzing social network and situation of individuals is **degree centrality**. Degree centrality refers to the number of links in or out of a node in the network (Freeman, 1979).

This measure deals with the position of individuals in a network. One person who can make skills and experiences for others is regarded as center (i.e., with higher degree centrality scores).

As it can be seen in Table 1, the Journal of American Medical Informatics Association ranked the first with average degree centrality of 20.74, Scientometrics with average degree centrality of 8.13 ranked the second and the Journal of the American Society for Information Science and Technology with average degree centrality of 4.77 ranked the third, while Library Quarterly ranked the last with an average degree of 0.66.

Table 1

Ranking of Information Science journal according to the centrality scores

Journal name	Degree	Closeness	Betweenness	Flow betweenness	Eigenvector
J AM MED INFORM ASSN	29.74	12.95	42.82	2.004	0.051
Scientometrics	8.13	1.21	62.69	1.32	0.022
J AM SOC INF SCI TEC	4.77	1.18	6.9	1.55	0.028
INFORM PROCESS MANAG	4.37	0.693	23.32	1.6	0.014
LIBR INFORM SCI RES	3.42	0.77	3.93	0.086	0.015
MIS Quarterly	3.35	0.85	113.18	1.21	0.025
MIS QUART	2.98	0.693	8.83	1.076	0.015
J INF SCI	2.51	0.55	5.13	0.811	0.013
GOV INFORM Q	2.21	0.71	2.68	0.759	-0.02
INFORM SYST J	2.02	0.41	16.08	0.938	-0.007

Journal name	Degree	Closeness	Betweenness	Flow betweenness	Eigenvector
J DOC	1.91	0.44	2.2	0.555	0.01
LEARN PUBL	1.78	0.692	0.56	0.644	-0.017
TELECOMMUN POLICY	1.47	0.46	3.5	0.776	-0.007
INFORM SYST RES	1.45	0.4	6.54	0.755	-0.011
COLL RES LIBR	1.41	0.45	0.37	0.409	-0.006
SOC SCI COMPUT REV	1.41	0.67	0.001	0.413	-0.015
J ACAD LIBR	0.75	0.65	0.42	0.809	-0.016
INT J INFORM MANAGE	0.69	0.393	0.2	0.226	-0.01
J INF TECHNOL	0.67	0.395	0.0005	0.252	-0.01
Library Quarterly	0.66	0.619	0.12	0.392	0.013

Closeness centrality is the distance of one individual to all other people in the network. The closer a person is to others, the more famous he/she would be. Individuals with higher closeness centrality scores probably get information very faster than other people because there are fewer intermediaries between them.

Closeness centrality measure is computed on the basis of the geodesic distance. This measure calculates the distance one node has from other nodes. This measure indicates accessibility, appropriateness and security of actors (Frank, 2002).

As can be seen in Table 1, the Journal of American Medical Informatics Association ranked the first with the average closeness centrality of 12.95 and Scientometrics with average closeness centrality of 1.21 ranked the second and the *Journal of the American Society for Information Science and Technology* ranked the third with average closeness centrality of 1.18.

Betweenness centrality views an actor as being in a favored position to the extent that the actor falls on the geodesic paths between other pairs of actors in the network. That is, the more people depend on me to make connections with other people, the more power I have (Hanneman & Riddle, 2005).

Average of betweenness centrality related to information science journals are shown in Table 1. MIS Quarterly with average betweenness centrality of 113.18 has the highest average of betweenness centrality and Scientometrics and the Journal of the American Medical Informatics Association with 62.69 and 42.82 ranked the second and the third respectively.

Phillip Bonacich proposed a modification of the degree centrality approach that has been widely accepted as superior to the original measure. The original degree centrality approach argues that actors who have more connections are more likely to be powerful because they can directly affect more other actors. This makes sense, but having the same degree does not necessarily make actors equally important (Hanneman & Riddle, 2005).

The flow approach to centrality expands the notion of betweenness centrality. It assumes that actors will use all pathways that connect them, proportionally to the length of the pathways. **Flow betweenness** is measured by the proportion of the entire flow between two actors (that is, through all of the pathways connecting them) that occurs on paths of which a given actor is a part. For each actor, then, the measure adds up how involved that actor is in all of the flows between all other pairs of actors (the amount of computation with more than a couple actors can be pretty intimidating!).Since the magnitude of this index number would be expected to increase with sheer size of the network and with network density, it is useful to standardize it by calculating the flow betweenness of each actor in ratio to the total flow betweenness that does not involve the actor" (Hanneman & Riddle, 2005). Flow centrality is similar to betweenness centrality except that, instead of considering only the shortest paths between pairs of nodes, we consider all paths.

Table 1 also represents the average flow betweenness of information science journals. As can be seen, Journal of the American Medical Informatics Association with 932.2 ranked the first and the Scientometrics with 322.34 and MIS Quarterly with 231.31 follow it respectively.

Eigenvector centrality is a measure of the importance of a node in a network. It assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the scores of the node in question than equal connections to low-scoring nodes (Bonacich, 1972). Formulas for these measures are mentioned in appendix.

Journal of the American Medical Informatics Association with 0.051 ranked the first and *the Journal of the American Society for Information Science and Technology* with 0.028 ranked the second and MI Quarterly with 0.025 ranked the third.

Correlation between centrality scores and impact factor (IF) of information science journals are showed in Table2. As it is displayed in Table2, all predictor variables except closeness centrality have significant correlation with Journal impact factor. Correlation between journal impact factor (JIF) and degree centrality with r=0.632, JIF and betweenness centrality with r=0.639, JIF and eigenvector centrality with R=0.686, JIF and flow betweenness with r=0.685 are totally significant at level p=0.001. Therefore, all parts of hypotheses of this section are confirmed. However, there is not a significant correlation between journal impact factor and closeness centrality at r=0.415 level.

Table 2

Correlations between centrality scores and Journal impact factor

Independent Variables		impact factor	Eigenvector	flow betweenness	betweenness	closeness	degree
impact factor	Pearson Correlation	---	.686**	.685**	.639**	.425	.631**
	Sig. (2-tailed)		.001	.001	.002	.062	.003
Eigenvector	Pearson Correlation		----	.709**	.372	.624**	.755**
	Sig. (2-tailed)			.000	.106	.003	.000
flow betweenness	Pearson Correlation			----	.247	.835**	.968**
	Sig. (2-tailed)				.295	.000	.000
Betweenness	Pearson Correlation				----	-.100	.129
	Sig. (2-tailed)					.674	.589
Closeness	Pearson Correlation					----	.817**
	Sig. (2-tailed)						.000
Degree	Pearson Correlation						-----
	Sig. (2-tailed)						
**. Correlation is significant at the 0.01 level (2-tailed).							

Results about analysis of centrality measures of authors in all examined journals showed that “GLANZEL” in Scientometrics with degree centrality scores 94 ranked the first, “BATES” in Journal of the American Medical Informatics Association with degree centrality scores 70 and “HERNON” in Library & Information Science Research with degree centrality Scores 77 ranked the second and the third. In general, actors such as “GLANZEL”, “BATES”, “HERNON” and the rest who have high centrality scores have more opportunity because have a more choice. They have access to most of sources in the network. Also, the top 3 authors based on other centrality measures are presented in Table 3.

Table 3

Top three authors according centrality scores

Row	Name	Journal	Scores
Degree centrality			
1	GLANZEL	Scientometrics	94
2	BATES	Journal of the American Medical Informatics Association	79
3	HERNON	Library & Information Science Research	77
Betweenes centrality			
1	GLANZEL	Scientometrics	2372
2	BENBASAT	MIS Quarterly	1246
3	KLEIN	Information Systems Journal	610
Closeness centrality			
1	MILLER	Journal of the American Medical Informatics Association	14.93
2	BATES	Journal of the American Medical Informatics Association	14.65
3	SAFRAN	Journal of the American Medical Informatics Association	14.65
Eigenvector centrality			
1	SCHWARTZ	Library & Information Science Research	0.692
2	HERNON	Library & Information Science Research	0.690
3	GLANZEL	Scientometrics	0.624
Beta centrality			
1	GLANZEL	Scientometrics	94
2	BATES	Journal of the American Medical Informatics Association	79
3	HERNON	Library & Information Science Research	77
Flow betweenness centrality			
1	ROUSSEAU	Scientometrics	5787
2	GLANZEL	Scientometrics	5340
3	MILLER	Journal of the American Medical Informatics Association	5062

Table 4 shows the correlation between centrality scores and the number of publications produced by researchers. As it is shown in Table 4, all predictor variables have significant correlation with total number of researchers' outputs in the field of information science.

Table 4

Correlations between authors productivity and centrality scores

		productivity	Degree	Eigenvector	Beta	Closeness	Betweenes	Flow Betweenes
productivity	Pearson Correlation	-------	.657**	.110**	.657**	.504**	.200**	.478**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
Degree	Pearson Correlation		----------	.254**	1.000**	.528**	.295**	.576**
	Sig. (2-tailed)			.000	.000	.000	.000	.000
Eigenvector	Pearson Correlation			-----------	.254**	.119**	.176**	.189**
	Sig. (2-tailed)				.000	.000	.000	.000
Beta	Pearson Correlation				-------	.528**	.295**	.576**
	Sig. (2-tailed)					.000	.000	.000
Closeness	Pearson Correlation					--------	.117**	.476**
	Sig. (2-tailed)						.000	.000
Betweenes	Pearson Correlation						-------	.780**
	Sig. (2-tailed)							.000
Flow Betweenes	Pearson Correlation							--------
	Sig. (2-tailed)							
**. Correlation is significant at the 0.01 level (2-tailed).								

Correlation between total number of publications and degree centrality equals r=0.675, betweenness centrality equals r=0.200, eigenvector centrality equals r=0.110, flow betweenness equals r= 0.468, beta centrality equals r=0.657 and closeness centrality equals r= 0.504, all of which are significant at level of p≤ 0.001.

To investigate the multiple relationships between predictor and criterion variables, multiple regression analysis is used. For this purpose, a multiple regression analysis was calculated using two methods of Enter and Stepwise.

Based on the results of multiple regression analysis with Enter method, coefficient of multiple correlation for the linear combination of predictor variables and productivity of researchers is equal to 0.649 (MR=0.694) and coefficient of determination is equal to 0.482 (RS=0.482) which is significant at the level of P<0.001.

Thus, hypothesis B is supported. The coefficient of determination obtained indicates that about 48% of the variance in research productivity variable is explained by the predictor variables. To determine the contribution of each variable, Stepwise method was used and the results showed in Table 5.

Table 5

Multiple correlation coefficients for degree centrality, closeness, flow betweenness, betweenness and Eigenvector with productivity by Stepwise

Predictors variable	MR	RS		(B) &(β)					(a)
				1	2	3	4	5	
Degree	0.657	0.432	F=2.644 P<0.001	β=0.657 B= 0.715 t= 51.42 P=0.001					2.504
Closeness	0.683	0.466	F=1.519 P<0.001	β=0.542 B= 0.59 t= 37.1 P=0.001	β=0218 B= 0.757 t= 14.97 P=0.001				2.351
Flow Betweenness	0.687	0.472	F=1. 037 P<0.001	β=0.498 B= 0.542 t= 29.52 P=0.001	β=0.195 B= 0.677 T=13.032 P=0.001	β=0.098 B= 0.002 T=6.28 P=0.001			2.38
Betweenness	0.692	0.479	F=799.38 P<0.001	β=0.479 B= 0.522 T=29.52 P=0.001	β=0.151 B= 0.524 T=9.31 P=0.001	β=0.248 B= 0.005 T=9.193 P=0.001	β=-0.152 B= -0.007 T=-6.79 P=0.001		2.49
Eigen vector	0.694	0.482	F=646.26 P<0.001	β=0.493 B= 0.537 T=29.85 P=0.001	β=0.152 B= 0.527 T=9.38 P=0.001	β=0.242 B= 0. 005 T=8.98 P=0.001	β=-0. 142 B= -0.007 T=-6.33 P=0.001	β=-.054 B= -4.57 T=-4.23 P=0.001	2.47

Also, according to Table 5, it can be seen that all five variables including degree centrality, closeness, flow betweenness, betweenness and Eigenvector are predictor of researchers' productivity. But given the values of the regression coefficients in term of the predictive power, are respectively, degree centrality β = 0.657 (p=0.001), closeness centrality β = 0.218 (p=0.001), betweenness centrality β = -0.152 (p=0.001), flow betweenness β =

0.098 (p=0.001) and eigenvector β =-0.054 (p=0.001) have more predictive power. Beta centrality has no role in prediction and has been removed from the regression equation.

The following equation shows the communication model in which the productivity of researchers is based on five variables to predict.

$Y= \alpha + (B_1X_1) +(B_2X_2) +(B_3X_3) + (B_4X_4) + (B5X5)$

$Y= 2.47 [0.537* X_1] + [0.527* X_2] +[0.005* X_3] +[-0.007* X_4] + [-4.57*X_5]$

Variables (degree centrality, closeness, flow betweenness, betweenness and Eigenvector) in the equation simultaneously have significant predictive power. As we can see, in the equation, there are five predictor variables and one criterion variable.

X_1, X_2, X_3, X_4 and X_5 as the five variables are respectively degree centrality, closeness, flow betweenness, betweenness and Eigenvector. The value of α based on regression analysis is 2.47. Coefficients B_1, B_2, B_3, B_4 and B5 respectively are 0.493, 0.152, 0.242,-0.142, -0.054.

The positive values indicate a direct relationship between the predictors and the criterion variables and negative values of some variables which indicate an inverse relationship between predictor and the criterion variables. In this way we can calculate the amount of productivity variable based on five variables. The higher rate of degree centrality reflects higher importance of this variable to predict criterion variable.

The reasons for success of a researcher with high centrality score

After identifying authors who had high centrality role in this research, the questionnaires with 3 open-ended questions were distributed to them and 137 questionnaires were returned. In this part the responses to questionnaires are analyzed.

Question 1: What are the main reasons of your success in this research which placed you in the center of co-author network?

After combining similar and eliminating duplicate answers, all responses to the first question follow:

Personal ability: hard work, perseverance and high spirit, strong motivation, start working in youth, curiosity to find new rules, skills of good writing, trying to be open-minded in work and areas of interest,

Collaboration or team working: Collaborate with different people, forming research team, international collaborations; communication and collaboration with colleagues, good colleague and co-author, generous colleagues, working with a team, the environment of work should be stimulating and exciting with young colleagues who are willing to learn and get help and experienced colleagues who can support them and prevent their despair, Identifying colleagues who one can have a good work relationship with them, this factor encourages discussing the ideas and makes it easier for establishing future research projects, team spirit, having too many people around, respecting to others’ opinions, rights and thoughts of others,

Work schedule: Having a timeline for doing research, working in productive good ideas for studies of interest to the community, continued focus on high quality research and ensuring that researchers have research outputs, having a clear focus of research is important to start with a strong base and gradually develop research projects that are feasible, approach-centered process

Interest: having an interest in this field, believing in the importance of the subject, believing in this idea that one person is getting promotion,

Access to data and financial support: access to a huge collection of data, take charge and work on research projects, the way that institute has been funded in the past,

Opportunity: luck, having good mentors, work on hot topics, spends a lot of time, one need to think outside the desired range and discover how seemingly unrelated disciplines help to your thought.

Question 2: In your opinion, in order to have a successful research team, in Library and Information Science, how many researchers should be included?

Answers to this question were almost similar and mostly agreed. The number of people participating in a research team is believed to be related to other factors such as skills that each person brings to the team. There should be people with whom you have good personal relationships. Number of people in a research team also depends on various other factors such as scope, research subject and nature as well as size of project. In general, some believed that two or three people are needed for small-scale projects while 4 to 5 people for large and interdisciplinary projects.

Some believed that, depending on the project, at least 5 people at different academic levels (professor, associate professor, assistant professor, administrator and planer) are needed; some others believed that about seven people, while most respondents believed that the team with three to five people includes an adequate number of people.

Question 3: What are those criteria that can be helpful in selecting members and organizing an active and productive research team in Information Science discipline?

Research team members should be motivated to do the work. They should have unique skills (writing, methodological, thematic expertise, etc.), and should complement each other. Each member of the team should bring their own skills inside the group. Teammates should be smart, hard-working, reliable and noble and their skills should be complementary. They should love each other and work together. Creativity and dedication, ability to work well with others (good interpersonal skills, flexibility), high work ethics, vibrancy, and ability to deliver timely work, loyalty and hard work as well as group membership are all among those characteristics needed. As they have different abilities, team members should be open to each other and support the team using complementary strengths and compatible work styles. They should also possess an appropriate range of experience to be able to cover the subject while they are interacting with the group members. It is expected that they be keen enough to listen to their teammates and participate in group’s discussion and share ideas as the whole is stronger than any single part.

Discussion

Information Science journals indexed in Thomson Reuter's database were examined in this study. Results showed that 22161 records were produced by 43739 authors. Findings from analysis of centrality of social network of co-authors revealed that these journals have relatively low average centrality, also the network had low density and there were little relationships between authors. It was also found that many of authors were not connected with each other.

Results from centrality analysis showed that Journal of the American Medical Informatics Association with average degree of centrality of 20.74 and MIS Quarterly with average of betweenness centrality of 113.18 had the highest betweenness centrality scores. *Journal of the American Society for Information Science and Technology* ranked first, both from the perspective of closeness centrality average of 12.95, and the average flow betweenness of 932.2. One of the noticeable journals in this area is Scientometrics that ranked second in all centrality measures. This fact shows that co-author social network of this journal has more cohesion than other journals in the scope of Information Science.

Results from this study also showed that the average of degree centrality scores related to the betweenness centrality in the journals of Information Science is more than the average of degree centrality scores in the journals of Organization and Management (Acedo et al, 2006) that equals to 2.68 in the degree centrality scores which is. 017.

Results of Otte and Rousseau (2002) showed that the degree of centrality in entire of network was 11% and betweenness was 47% in Sociological abstracts, Medline and Psyc INFO databases, so results of this study, in comparison with Otte and Rousseau (2002), show that the former is at a higher level but it is lower than the results of GOSSART & ÖZMAN (2009) study. They studied co-author network of social science in Turkey in SSCI and ULAKBIM databases and betweenness centrality for these databases was 0.0006 and 0.00013 respectively.

Result of this study is also higher than the results of Gómez et al. (2008) about co-author networks in three areas of study in Madrid whose betweenness centrality was higher than 0.5, the average of closeness scores equaled 2.32 and the average of degree was 6.

On the other hand, results showed that co-author networks are widely composed of separate groups in most of Information Science journals. Besides, there was little interface between these authors. This provides very little opportunity for dissemination of knowledge. To solve this problem, it is suggested that authors of Information Science journals make their research groups to make the co-author social networks between themselves denser and increase the flow of knowledge dissemination.

The results also showed there was significant correlation between journal's Impact Factor

(IF) and the average of centrality scores which express that journals with higher IF have more collaboration in writing articles, in addition there are more relationships between journal's authors.

So, we can conclude that the journals which have more collaboration in their articles get more citations. We should also point out that whatever these collaborations are regional or international or whatever the authors of the articles are from various geographical regions, they get more citations. For the most part, the works of important and illustrious authors get more citations due to their reliability and influence on colleagues and students in similar subject areas. Besides, printing the works of these authors in journals will lead to more citations and finally more Impact Factor (IF) for these journals.

The results also showed that there was significant correlation between centrality of factors and productivity. It means that the more a person is involved in centrality of factors and more centrality scores, the more influence he/she has and this leads to more productivity and scientific outputs. Moreover, regression reports direct relationship of degree, closeness and flow betweenness and inverse relationship of betweenness and Eigen vector centrality on productivity of researchers.

In general, we can say "Glanzel" is the most influential author between authors of Information Science journals because he has the highest centrality scores. The results about studied journals showed that Journal of American Medical Informatics and scientometrics had the highest centrality scores in terms of centrality scores. This is perhaps for the reason that these journals are mainly specialized (scientometrics only prints in area of Scientometric and Journal of American Medical Informatics prints the articles in Medical Informatics).

Finally, questionnaire's results of those researchers who have high centrality scores indicate that forming a harmonious research team is one of the main reasons of researchers' success. In fact, when forming a research team, several criteria such as research ethics, respects to teammates' rights, solidarity with team members, loyalty and agreement between teammates, having an approach-centered process as well as punctuality should be fully taken into consideration.

Appendix:
formulas of centrality measures (Marsden, 2002)

Degree centrality

$$C_D(p_i) = \sum_{k=1}^{N} a(p_i, p_k)$$

Closeness centrality

$$C_C(p_i)^{-1} = \sum_{k=1}^{N} d(p_i, p_k)$$

Betweenness centrality

$$C_B(p_i) = \sum_{j=1}^{N} \sum_{k=1}^{j-1} b_{jk}(p_i)$$

Eigenvector centrality

$$x_i = \frac{1}{\lambda} \sum_{j \in M(i)} x_j = \frac{1}{\lambda} \sum_{j=1}^{N} A_{i,j} x_j$$

Flow betweenness

$$C_F(x_i) = \sum^{n} \sum^{n}_{j<k} m_{jk}(x_i).$$

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