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Research Article

Social Influence, Research Productivity and Performance in the Social Network Co-authorship: A Structural Equation Modelling

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ABSTRACT

Social influence refers to the interaction of one person with other researchers in the/a social network and is calculated by the analysis of co-authorship networks and centrality indices. The purpose of the present study was to investigate the relationship between social influence and productivity with the performance of the researchers in the area of throbbing headaches. Bibliometric indicators, social network analysis techniques and structural equation modeling (SEM) were employed. The population included 35050 records of throbbing headaches indexed in the Web of Science from 2005 to 2017. Analysis of the relationship between social influence scores and the researchers' performance showed a positive correlation between the degree and betweenness centrality with the performance of the researcher and no correlation between closeness centrality and performance; meaning the greater the degree and betweenness centrality of the authors', the greater effectiveness. Variance regression analysis revealed nearly 56 percent of the researchers' productivity variance was determined by the degree and betweenness centrality. In addition, the results indicated a correlation between social influence and ideational influence indicators, meaning the researchers with the higher social influence possess higher ideational influence. Based on the findings of the present study, using a combination of indicators to examine the effectiveness of an author in terms of productivity and performance is argued whether it can help identify a successful researcher in a scientific field in a more realistic and creative way.

Keywords: Social influence, Ideational influence, Research productivity, Research performance, SEM.

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INTRODUCTION

As one of the highly researched issues in recent years, co-authorship and scientific collaborations have drawn a great deal of attention in academic circles. The increase in the publication of multiple-author articles and the consequent fall in release of single-author papers is one of the most probable reasons for that attention.,[1] In other words, the rise of scientific exchanges and social interactions has led to a dramatic increase in research collaborations.[2] Researcher productivity enhances positively via collaboration to which significant attention has been paid in recent studies, focusing on researcher influence and recommender systems.[3]

Universality of collaborations in various sciences is widely studied recently, while a lack of detailed data is perceived in how teams collaborate within themselves.[4] The complex multi-discipline research questions require the collaboration of various experts.[5]

There are different reasons behind conducting a shared research project, among which are the accelerating pace of specialization in scientific researches, the interdisciplinary nature of the majority of research projects and the priority of inter-organizational projects in funding opportunities.[6]

According to Leifeld *et al*.[7] co-authorship is one of the most common forms of scientific collaboration, resulting in some networks that are among the most evident forms of collaborative structures.[6] Co-authorship seems to be an intriguing topic for researchers interested in studying scientific collaboration. A testimony is that since early 1980s, it has been employed as a tool to evaluate scientific partnership. Nowadays, this quality has given co-authorship a satisfactory level of formal and content validity, owing to the fact that if the names of two or more authors appear in a single paper, it can be justified that these authors have somehow collaborated.[8] Therefore, through the investigation of co-authorship relationships among researchers in a certain field, one can determine the finest scholars in the field based on their distinguished social activities, meaning their social influence defined as the way an individual interacts with his colleagues in co-authorship social networks.

However studying collaboration networks reveals the reasons behind their formation, it is challenging since a full-time observation of which is out of access.[9]

Researcher social influence may be a product of their scientific collaboration. The individual scientist social influence has been examined considering one collaboration category. The problematic part is that various collaborations exist resulting in diverse effects on social influence.[5]

A network of communications, also known as a social network, is formed as a result of scientific collaborations between scientists, organizations, countries, etc. in the same or different fields of science and the ensuing relationships established between them. A social network is essentially a set of elements and the binding relationships between them. The elements can be individuals or entities such as groups, organizations and families. In the present paper, the elements are the authors and the authorship of the articles is the relationship between them. Co-authorship networks are considered as an important category of social networks and can be widely used to determine the structure of scientific collaborations and the status of researchers individually.[10]

Social network analysis is often applied to analyze co-authorship relations. The nodes in the network are the authors and the interactions between them form the network links. Thus, the network of authors can be considered as a specific type of social networks.[11]

One of the results of this method is the 'centrality' analysis. The centrality constitutes the kinds and numbers of relations a member of a network has with the other members of the network. While investigating the centrality indices referring a researcher in a scientific network and making a related author profile, their social influence can be appraised.[12] These centrality indicators include degree centrality (the number of ties a node has), betweenness centrality (the degree to which nodes stand between each other), closeness centrality (a researcher's distance from the others on the network) and so on. By studying the centrality measures of the assorted members of the community, one can arrive at a set of measures that assesses the connectedness of each member of a research community.[12]

The co-authorship relationships are analyzed using social network analysis (SNA) in order to capture and appraise connectedness.[13] According to Merrill and Hripcsak,[14] the social network can be used to characterize and describe the community structure of its members. A profile of connectedness useful for comparing scholars with one another can be obtained by calculating the centrality measures of degree, betweenness and closeness.[12] The influence is used to evaluate scientific outputs.[15] The discovery of relationships between resources and scholars and the interpretation of the relationships among them can help distinguish the most influential people, particularly in interdisciplinary sciences. Those people are important as the result of linking between several scientific fields.

In a great number of studies[16,17] performance has been defined as the number of citations. While in some others, it refers to the quality of research.[18] As the impact of a researcher is also examined through the citations to his works, in the present paper, the focus has been on the number of citations. Moreover, the productivity of a researcher is typically determined by the number of research studies he has conducted. Thus, productivity is considered to be the number of articles in the present study.

Truex *et al*.[19] identified two forms of influence. The first one is ideational influence (passive: who is using the work of the researcher?), which also indicates how dominant the researcher's ideas may be in his field,[20] and the second one is social influence (active: who does the one work with?). Ideational influence is mattered based on citation indicators and scholars have operationalized it with the Hirsch family indices,[21-23] Co-authorship relations are analyzed using SNA for both scholars and journals to evaluate connectedness.[13]

Since Hirsch's,[22] *h*-index was suggested, some researchers have supplied the *h*-index or other citation-based indicators on their personal websites. Li,[10] defined the practice of displaying citation counts as displaying citation-based indices.

The *h*-index has lots of specific features.[24] For instance, evaluating and focusing on the quantity and effectiveness of articles is easy using the *h*-index. Moreover, many papers have been written in this field and some of the new indices developed on the basis of the *h*-index are trying to get over its shortcomings. For example, it has been shown that the index does not indicate a sensitivity to low citation papers.[25] In order to figure out the *h*-index problems, Egghe[21] proposed the '*g*-index' which gives more weight to the highly-cited papers.[12] The *g*-index has the most discriminating power among *h*-index family indicators.[24] The value of the *g*-index is always higher than the *h*-index. Therefore, it is more suitable for discriminating researchers' performances.[26] Another indicator is contemporary *h*-index (c-*h* index), introduced by Sidiropoulos, Katsaros and Manolopoulos,[23] which gives more weight to the age and citations to recently-published papers. Using the c-*h* index, you can eliminate the effects of time on citations and compare them among articles published in different years.[12]

By using the three indices of h, c-h and g-h, we can make a profile of scholars' ideational influence helpful to compare their relative influence. One aspect that previous research consistently highlights is that one should not rely on an individual metric when appraising a researcher's impact; rather, one should use a set of metrics to measure that.[27-29]

In addition, a researcher's influence is not bound to his/her citations. The manner of interacting with other researchers in the field is at work in his/her scientific influence in a scientific network.[19] "Some researchers have the power of attracting other researchers and influencing their thoughts by their strategic placement in the social network of a scientific field".[29] The ability to influence others through social interaction processes is called social influence.[19]

Centrality indices are used to calculate the social influence. Due to the dynamic nature of medical science and its direct link to the health and life of human beings, it has always been an area of great interest in scientific disciplines. Meanwhile, migraine, which is directly related to human brain and nerves, plays a significant role in this subfield of medical sciences.

Headache is the most common neurological disorder in outpatient visits and is the seventh cause of the inability to live among different individuals,[30] due to stretching, displacement, inflammation and dilation of buildings sensitive to pain in the head or neck. Headaches can be due to different causes such as the limited number of sensitive buildings. There are two main types of headaches, migraine and tension headaches. Among the causes of headaches, migraines are the most common chronic headache. It is a common disorder with a family background characterized by periodic headaches, usually one-sided and often throbbing.[31] Jay and Barkin,[32] declared that migraine is a neurovascular disorder, both scalp tenderness and referred pain have been detected in migraine patients. Migraines are important due to their high prevalence and disabling severity. Several seminal papers in Europe and the United States showed that the incidence of migraine in women is about 20% and in men is about 6%. Moreover, in a study on migraine in the United States in 1999, it was found that 27.9 million Americans suffered from migraines.[31] Migraine headaches have been quite predominant during the life of human societies. Researchers in this field, along with other researchers from various medical trends, have carried on research on the subject, which over time has led to the formation of its scientific structure. Sharing ideas in their scientific collaboration, researchers can exert mutual influence over the quality of each other's work. Hence they can benefit both from their own specialized skills and the achievements of others in the group. This can result in quantitative and qualitative growth of research outputs in a particular field.[33]

According to Vinkler,[24] many indicators can be used to evaluate researchers, while only a few of them may show the different aspects of the effect. The use of such specific indicators helps policy makers to use accurate scientific tools to rank researchers.

Scientific (sub) disciplines may show various specific features differing from those of the scientific network as a whole, thus studying their structures via scientific co-authorship is considerable.[34]

Various factors affect the researcher productivity. The literature of co-authorship supports the researchers who are members of coherent research teams and have high productivity and performance. Therefore, the present study aimed to explore the relationship between social influence and the level of productivity and performance in the researches on throbbing headache.

Easy and accessible exchange of ideas pushes forward the advance of knowledge via providing the opportunity to challenge and examine ideas, the identification of the most valuable of which is possible in an open environment.[20]

Gaining promotion and tenure (P&T), grants and awards depend on the evaluation a research output receives. Thus the research topic, methods and approaches are directly affected by the attempt to get a positive evaluation. The number of articles published in high rank journals is a pragmatic standard for quality evaluation. Since all the published articles get reviewed by a team of professionals, their quality need not be assessed all over again. However, the method has its deficiencies.[35]

Exploring and interpreting author-resource relationship with in order to identify influential figures has become increasingly important, especially in interdisciplinary sciences involving the integration of two or more established disciplines. In recent decades, a significant rise in the development of these sciences occurred. The ever-expanding boundaries of scientific areas of expertise and the confluence of scholarly ideas and endeavors have played an important role in the formation and development of the aforementioned sciences. Hence, it is assumed that the collaborative nature of interdisciplinary research areas such as migraine research studies can be revealed by the analysis of scholarly influence of scientists and researchers; possibly one of the main reasons for the popularity of the Scholarly Influence Model and its components in various research domains. Accordingly, since the interdisciplinary nature of migraine research studies paved the way for interacting with several other sciences and since scientometric studies come to the spotlight, the urgent necessity of employing these studies in medical research areas is felt. Therefore, the present study aimed to raise the awareness among policy-makers and researchers in the area of throbbing headaches, inform them of the recent research findings and, in the case of any shortcomings, undertake major initiatives to solve them and enhance scientific productivity.

The present study aimed to investigate the relationship between social influence and productivity with the researcher performance in the area of throbbing headaches. The specific objectives of the present study are determining the relation between productivity and performance, examining the relation between researcher social influence and their performance, identifying the relation between researcher social influence and their productivity and recognizing the relation between social and ideational influence.

MATERIALS AND METHODS

The present study has an applied scientometric approach, conducted by employing co-authorship network analysis techniques, citation analysis and social network analysis techniques. The data were retrieved from Web of Science online database. The statistical population consisted of the whole scientific production in the field of throbbing headaches, indexed in the Web of Science from 2005 to 2017, the year 2005 was chosen since the first issue of the core journal in throbbing headache field, Clinical Neurology, was published then. The Thesaurus for Medical Subject Headings (MESH) was used to determine the search terms. The term *migraine* was searched in the thesaurus with the aim of finding Migraine Tree and selecting more specific and broader terms (BT). These terms are selected mainly because the related terms (RT) can form a separate cluster of words. For example, in order to investigate the scientific production status in the field of *Tension Headache*, the term *Tension Headache* and its specific and sub-specific terms need to be collected, put in a folder and analyzed by some software tools. The present study presented a general picture of scientific production in the field of Migraine studies. Determining different branches of migraine was the main step in data collection process. In the above mentioned thesauri, the term *Migraine* has 8 specific terms and the total number of 22 terms. They have been identified to achieve a complete set of data in the search strategy. Then, the terms extracted from the Personal Brain Software (Version 9.0.207.0), which provides a representative sample of the given statistical pollution, were entered with the aim of drawing the Migraine Tree. In order to cover the whole Migraine-related documents, all the terms extracted from the thesauri were examined based on the deletion of the repeated cases.

The required data were collected by conducting a search based on the 22 descriptors available on the drawn Migraine tree and the OR operator in the general search section of the Web of Science (Version 5.25.1). Considering the time period from 2005 to 2017, the researcher used the subject field, selected all the options available on the Web of Science core collection without any limitation of language, document type and country name and entered the following descriptor in the search field.

"migraine disorders" OR "throbbing headache" OR "migraine" OR "headache" OR "cluster headache" OR "neuralgic migraine" OR "histamine cephalgia" OR "sick headache" OR "splitting headache" OR "stress headache" OR "tension headache" OR "tension vascular headache" OR "vascular headache" OR "megrim" OR "abdominal migraine" OR "basilar artery migraine" OR "basilar migraine" OR "basilar- type migraine" OR "classic migraine" OR "classical migraine" OR "migraine with aura" OR "migraine without aura"

Then, the documents recognized as *Article*, *Proceedings Paper* or *Review* were chosen. In the present study, a total of 35050 records related to the throbbing headache field were detected and entered the loading phase. The data collected by Excel software, Bibexcel (2014-03-25) and Ucinet (Version 6.627) have been analyzed and the results of which are presented in tables, charts and figures.

The authors of the articles were extracted and consolidated from the documents under study using special commands from the Boyle Excel software. In addition, all the authors of the articles were considered, not merely the first one. The value of matrix cells and the number of collaborations of two authors are taken into account.

Regarding the large number of authors in the study, based on the Bradford Law, authors whose articles were 16 or more were selected; thus, 655 authors were analyzed. The symmetric matrix was used and the cut point was considered. To measure the ideational influence of a researcher, the indexes of *h*, *h-c* and *g-h* were calculated. To calculate the social influence indicators of an author using the Ucinet software to measures of centrality. The excel command was used to extract the document citations.

For the components of ideational and social influence, Cronbach's alpha was 0.895 and 0.801, respectively. As the above values are more than 0.7, they have an acceptable level of reliability. To analyze the collected data and to evaluate the relationship between the variables of the research, the researcher has employed inferential statistics including Pearson correlation coefficient and linear regression, using the SPSS software. Moreover, structural equation modeling was obtained using the LISREL.

RESULTS

Table 1 shows the most cited authors in the field of throbbing headaches. As can be seen Lipton RB, Goads by PJ and Bigal ME have the highest number of citations.

Pearson correlation coefficient was used to answer the question. The results are presented in Table 2.

Based on the results presented in Table 1, the level of significance is 0.00 and is smaller than 0.05. Therefore, there is a significant relationship between these two variables. The correlation coefficient between the productivity and the performance is 0.788, showing a high level of correlation between these two variables since the correlation coefficient is close to 1. The sign of the correlation coefficient determines the direction of the relation between the variables; in case the correlation coefficient sign is positive, there is a direct relationship between them, meaning if the productivity increases, the performance will rise and vice versa. This suggests that researchers, in addition to the increase in their productivity, have been able to improve the quality of their work and this quality has increased the visibility of the papers, thus received more citations.

Table 1: Distribution of citation of top 50 Authors.

S.No	Author	Papers	Citations	S.No	Author	Papers	Citations
1	Lipton RB	256	13965	26	Evers S	111	3028
2	Goadsby PJ	260	10225	27	Arendt-Nielsen L	59	1690
3	Bigal ME	153	6859	28	Zwart JA	65	2698
4	Diener HC	240	7257	29	Fuh JL	98	2171
5	Ferrari MD	193	6157	30	Pareja JA	62	1801
6	Schoenen J	108	5128	31	Leone M	73	1835
7	Burstein R	85	5477	32	Lanteri-Minet M	71	1939
8	Dodick DW	138	5695	33	Hagen K	77	2592
9	Olesen J	192	7047	34	Edvinsson L	68	1518
10	Silberstein SD	120	5479	35	Coppola G	68	1561
11	van den Maagdenberg AMJM	126	4251	36	Buse DC	72	1831
12	Jensen R	93	4193	37	Cuadrado ML	67	1392
13	Stovner LJ	110	6769	38	Rapoport AM	72	1564
14	Kurth T	94	3793	39	Straube A	112	1304
15	Bussone G	216	3439	40	Silberstein S	54	1495
16	May A	110	3569	41	Pascual J	82	1946
17	Katsarava Z	116	3256	42	Linde M	75	2113
18	McHutchison JG	42	5741	43	Brandes JL	30	1326
19	Wang SJ	150	3075	44	Carotenuto M	27	850
20	Terwindt GM	87	2918	45	Schurks M	51	1745
21	Aurora SK	56	2555	46	Esposito M	28	831
22	Fernandez-de-las-Penas C	110	2100	47	Steiner TJ	82	4184
23	Nappi G	107	3244	48	Dodick D	35	2292
24	Ashina M	104	2217	49	Bendtsen L	52	1423
25	Bousser MG	49	3678	50	Svensson P	45	1331

Table 2: Correlations between productivity and performance.

		(No. of citations)
Productivity (number of articles)	correlation coefficient	0.788
	Significance level	0.00
	numbers	655

Based on the results obtained from the regression equation for multivariate analysis, the independent variable, i.e. social influence, was considered to predict the value of the dependent variable, i.e. performance. The regression prediction model has two stages. In this analysis, all the independent variables are entered into a step-by-step process. Regarding Durbin-Watson's statistics, the research model had no coefficient problem, since the Durbin-Watson value is between 1.5 and 2.5. Moreover, based on the residual graph against the predicted values, the assumption of the equivalent variance of the remainder was accepted. The results of Table 2 show that the regression prediction equation has two stages. The first variable entered into the equation is degree centrality. The results indicate a high level of correlation ($R = 0.69$) between this degree variable and the performance, meaning the increase in the degree centrality of authors can increase their performance. In the second stage, the betweenness centrality was entered into the equation and the value of *t* for this variable was 9.999 and the significant coefficient was 0.00 and the correlation was 0.68. The closeness centrality could not pass the desired criterion and entered the model, due to its significant amount that is 0.89 of the model, it was eliminated. There is no significant correlation between the two centrality and performance variables. Based on the second stage, the correlation of the model increased and reached a high level ($R = 0.74$). The value of the determination coefficient in the second stage showed that, in total, the degree and betweenness centrality variables express 56% of the variability of the dependent variable i.e. performance.

Other statistical indices of intra-equation variables such as Beta for standardized scores as well as t statistics are presented in Table 3. The coefficient B showed that in the first stage, one-unit increase in the degree centrality can add 15.497 scores to the variable performance. In the second stage, one-unit increase in the betweenness centrality can add 0.261 scoresto the variable performance.

Based on the results obtained from the regression equation for multivariate analysis, the independent variable, i.e. social influence, was used to predict the value of the dependent variable, i.e. productivity. The regression prediction model has two stages. In this analysis, all independent variables are entered into the step by step process. Regarding the amount of Durbin-Watson's statistics, the research model has no coefficient problem. Moreover, based on the residual graph against the predicted values, the assumption on the equivalence of the variance of the remainder was accepted. The results of Table 3 show that the regression prediction equation has two stages. The first variable entered into the equation is degree centrality. The results show that there is a high correlation between this variable and productivity ($R = 0.79$), meaning the higher the centrality of authors, the more productive they would be. In the second stage, the betweenness centrality variable is entered into the equation and the value of t for this variable is 12.106 and the significant coefficient is 0.00 and the correlation is 0.750. The closeness centrality variable could not cross the criterion and enter the model. Therefore, it is eliminated as its high significance is 0.49, showing no significant correlation between the closeness centrality and productivity. In the second stage, the correlation of the model increased ($R = 0.83$) which is a high index. The value of the determination coefficient in the second stage confirmed that, in total, the degree and betweenness centrality variables showed 70% of the variability of the dependent variable.

Other statistical indices for intra-equation variables such as beta for standardized scores and t statistics are presented in Table 4. The coefficient B shows that in the first stage, one-unit increase in the degree centrality can add 0.411scores to the variable productivity. In the second stage, one-unit increase in the betweenness centrality can add 0.006 scores to the productivity.

Table 3: Multiple Correlation coefficients of social influence with performance.

Level	Variables	B	Beta	T	R	R^2	D-W	Added value toR^2	Sig
1	Degree centrality	15.497	0.698	24.901	0.698	0.487	1.789	-	0.00
2	Betweenness centrality	0.261	0.375	9.999	0.745	0.555		0.068	0.00

Table 4: Multiple Correlation coefficients of social influence with productivity.

Level	Variables	B	Beta	T	R	R^2	D-W	Added value toR^2	Sig
1	Degree centrality	0.411	0.792	33.106	0.792	0.601	2.169	-	0.00
2	Betweenness centrality	0.006	0.376	12.106	0.834	0.695		0.094	0.00

Based on the results, the structural relationship between social influence and ideational influence, the structural equation modeling (SEM) was used and the results are depicted in Figures 1 and 2 and Table 5.

Table 5: Indicator range and goodness fit.

Fitness Index	Type of index	Good fit	Amount calculated
χ^2 / df	Absolute Fit Indices	$0 \leq \chi^2 / d_f \leq 3$	0.548
RMSEA		0 ≤ RMSEA ≤ 0.08	0.024
GFI		0.90 ≤ GFI ≤ 1	0.91
AGFI		0.90≤ AGFI ≤ 1	0.90
SRMR		0 ≤ SRMR ≤0.05	0.043
IFI	Comparative Fit Indices	0.90 ≤ IFI ≤ 1	0.96
NFI		0.90 ≤ NFI ≤ 1	0.95
NNFI		0.90 ≤ NNFI ≤ 1	0.93
CFI		0.90≤ CFI ≤ 1	0.90
PGFI	Parsimonious Fit Indices	PGFI >0.5	0.74
PNFI		PNFI >0.50	0.68

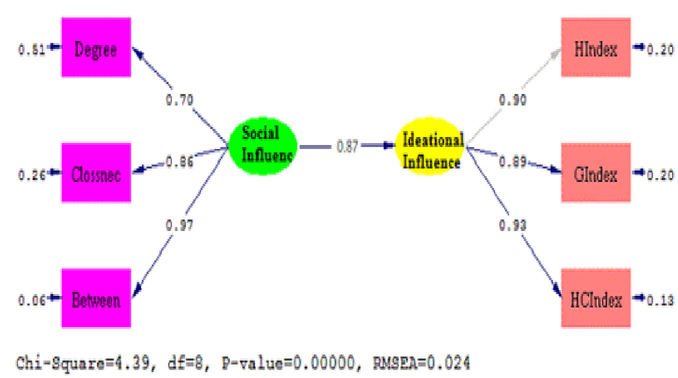

Figure 1: The standard structural modelling based on the significance of coefficients: Social influence (SI), Ideational influence (II).

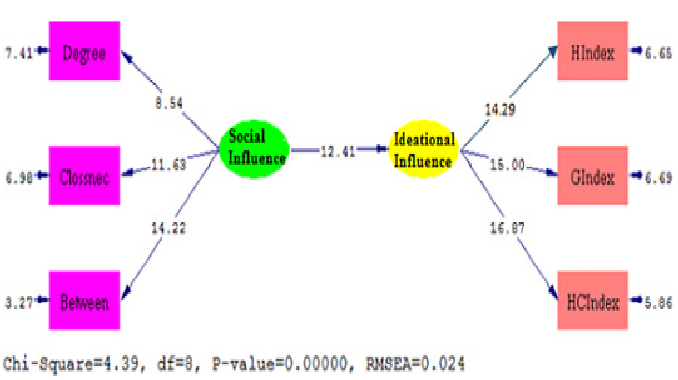

Figure 2: Significant coefficient between social influence and ideational influence.

Figures 1 and 2 demonstrate the structural relationship between the variables of the research model based on the Structural Equation Modeling. Based on this model, the direct and significant effect of social influence on ideational influence with respect to the path coefficient was 0.87, t amount of 12.41 and the significance level was 0.05, because t was out of the range of 1.96, -1.96.

The qi-2 value is 0.548 and less than 5. Moreover, the root mean square error of approximation (RMSEA) is 0.044 and less than 0.08. Regarding the fact that the incremental growth index (IFI), normative fitness index (NFI), normality index (NNFI) and comparative fit index (CFI) are more than 0.90, the relationship between social and ideational influence indicators was accepted and confirmed in terms of the fitting results.

DISCUSSION

The results of Pearson correlation coefficient showed that there is a direct relation between productivity i.e. the number of papers and performance i.e. the received citations. In addition, the results of the regression equation for multivariate analysis showed a positive and high correlation between the degree and betweenness centrality with performance, as the one-unit increase in the centralities can enhance the researcher's performance, which is in line with the results of Glanzel and Schubert,[36] Stringer,[37] and Soheili *et al*.[29] In their contributions, they found that researchers with more centrality scores had better research performance.[36,37,29] Further, the results of Hill,[38] corroborate with those of the present study. The results of Hill's[38] study suggested a positive correlation between productivity and the centrality score in computer science in America. Furthermore, the present results confirm those obtained by Badar, Hite and Badir[39] who showed that there is a relationship between the degree and closeness centrality with the performance of Pakistani researchers of chemistry. However, the results on closeness centrality showed that there was no significant correlation between the closeness centrality and performance. They revealed a positive and significant relationship between ideational and social influence, in that social influence had a significant positive effect on ideational influence. Such a relationship can be attributed to the fact that researchers with stronger social interactions will be better able to collaborate with other researchers and enhance the quality of their work, resulting in better co-authorship and indicators. One consequence of higher quality research is to obtain more citations and thus to improve the *h*-index family indices. The relationship between co-authorship centrality and citation performance has been studied widely. For instance, Sadatmousavi *et al*.[40] indicated that higher network centrality had higher citation absorption capacity. In addition, Yan and Ding[41] and Li, Liao and

Yen[42] concluded that higher betweenness centrality increases the researcher citations. In a co-authorship network, the researcher who has a high closeness centrality has a quicker access to all the other researchers in the network, thus he can access his required sources more appropriately. Better access to resources can in some cases increase the quality of publications and since publishing quality increases the number of citations, one prediction is that in a co-authorship network, researchers who are close to the other members i.e. have higher closeness centrality, can obtain more citations for their publications.

This finding is in line with the results reported by Kong *et al*. who found that the academic social impact should also be considered to mine the most prolific researchers.[42] Diverse of activities of a scientist build up his/her influence on the scientific collaboration network. Avocations, achievements, style and work habits may affect the researcher social influence.[5]

Based on the findings of the present study, applying some integrated indicators for measuring the scientific influence of a researcher in a certain scientific field can help better identify more brilliant and outstanding scholars in the scientific field. A large number of research studies on the effectiveness of researcher's employed the number of articles to evaluate the influence of the researchers. Furthermore, in some of the recent studies, citation-based indicators such as the emergency index and *h*-index have been applied to measure a researcher's scientific influence. The present study, however, like the research carried out by Soheili *et al*.[29] employed the integrated indices to determine a researcher's scientific influence. Moreover, the structural equation modelling showed a direct and positive relationship between the social influence and the ideational influence, which is in line with the results of Soheili *et al*.[29] Thus, any author who has a higher ideational influence can also havea higher level of social influence on his/her co-authorship network.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

ABBREVIATIONS

RMSEA: Root Mean Square Error of Approximation; **GFI:** Goodness of Fit Index; **AGFI:** Adjusted Goodness of Fit Index; **SRMR:** Standardized Root Mean Square Residual; **IFI:** Incremental Fit Index; **NFI:** Normal Fit Index; **NNFI:** Non-Normal Fit Index; **CFI:** Comparative Fit Index; **PGFI:** Parsimonious Goodness of Fit Index; **PNFI:** Parsimonious Normed Fit Index.

REFERENCES

1. Youtie J, Bozeman B. Dueling co-authors: How collaborators create and sometimes solve contributor ship conflicts. Minerva. 2016;54(4):375-97.
2. Li M, Zhuang X, Liu W, Zhang P. More Stable Ties or Better Structure? An examination of the impact of Co-author network on team knowledge creation. Frontiers in Psychology. 2017;8(1484):1-9.
3. Kong X, Mao M, Jiang H, Yu S, Wan L. How does collaboration affect researchers' positions in co-authorship networks?. Journal of Informetrics. 2019;13(3):887-900.
4. Lu C, Zhang Y, Ahn YY, Ding Y, Zhang C, Ma D. Co-contributorship Network and Division of Labor in Individual Scientific Collaborations. Journal of the Association for Information Science and Technology. 2019;1-17. https://doi.org/10.1002/asi.24321
5. Jiang J, Shi P, An B, Yu J, Wang C. Measuring the social influences of scientist groups based on multiple types of collaboration relations. Information Processing and Management. 2017;53(1):1-20.
6. Dehdarirad T, Nasini S. Research impact in co-authorship networks: A two-mode analysis. Journal of Informetrics. 2017;11(2):371-88.
7. Leifeld P, Wankmüller S, Berger VT, Ingold K, Steiner C. Collaboration patterns in the German political science co-authorship network. PloS One. 2017;12(4):e0174671.
8. Ponomariov B, Boardman C. What is co-authorship?. Scientometrics. 2016;109(3):1939-63.
9. Li Y, Zhang D, Luo P, Jiang J. Interpreting the formation of co-author networks via utility analysis. Information Processing and Management. 2017;53(3):624-39.
10. Liu X, Bollen J, Nelson ML, DeSompel HV. Co-authorship networks in the digital library research community. Information Processing and Management. 2005;41(6):1462-80.
11. Li EY, Liao CH, Yen HR. Co-authorship networks and research impact: A social capital perspective. Research Policy. 2013;42(9):1515-30.
12. Cuellar MJ, Vidgen R, Takeda H, Truex D. Ideational influence, connectedness and venue representation: Making an assessment of scholarly capital. Journal of the Association for Information Systems. 2016;17(1):1-28.
13. Vidgen R, Henneberg S, Naudé P. What sort of community is the European Conference on Information Systems? A social network analysis 1993-2005. European Journal of Information Systems. 2007;16(1):5-19.
14. Merrill J, Hripcsak G. Using social network analysis within a department of biomedical informatics to induce a discussion of academic communities of practice. Journal of the American Medical Informatics Association. 2008;15(6):780-2.
15. Soheili F, Khasseh AA, Mousavi CA, Tavakolizadeh-Ravari M. An evaluation of information behaviour studies through the Scholarly Capital Model. Learned Publishing. 2018;31(2):121-9.
16. Fu HZ, Long X, Ho YS. China's research in chemical engineering journals in Science Citation Index Expanded: Abibliometric analysis. Scientometrics. 2014;98(1):119-36.
17. Borgman CL. Scholarly communication and bibliometrics. Sage Publications; 1990.
18. King J. A review of bibliometric and other science indicators and their role in research evaluation. Journal of Information Science. 1987;13(5):261-76.
19. Truex D, Cuellar M, Takeda H, Vidgen R. The scholarly influence of Heinz Klein: Ideational and social measures of his impact on IS research and IS scholars. European Journal of Information Systems. 2011;20(4):422-39.
20. Cuellar M, Truex D, Takeda H. Reconsidering counting articles in ranked venues (CARV) as the appropriate evaluation criteria for the advancement of democratic discourse in the IS field. Communications of the Association for Information Systems. 2019;44:188-203.
21. Egghe L. Theory and practice of the g-index. Scientometrics. 2006;69(1):131-52.
22. Hirsch JE. An index to quantify an individual's scientific research output. Proceedings of the National Academy of Sciences of the United States of America. 2005;102(46):16569-72.
23. Sidiropoulos A, Katsaros D, Manolopoulos Y. Generalized Hirsch *h*-index for disclosing latent facts in citation networks. Scientometrics. 2007;72(2):253-80.
24. Vinkler P. Core indicators and professional recognition of scientometricians. Journal of the Association for Information Science and Technology. 2017;68(1):234-42.
25. Alonso S, Cabrerizo FJ, Herrera-Viedma E, Herrera F. Hg-index: A new index to characterize the scientific output of researchers based on the h-and g-indices. Scientometrics. 2010;82(2):391-400.
26. Rosenstreich D, Wooliscroft B. Measuring the impact of accounting journals using Google Scholar and the g-index. The British Accounting Review.

2009;41(4):227-39.

27. Bornmann L, Mutz R, Daniel HD. Are there better indices for evaluation purposes than the *h* index? A comparison of nine different variants of the *h* index using data from biomedicine. Journal of the American Society for Information Science and Technology. 2008;59(5):830-7.
28. Mingers J, Macri F, Petrovici D. Using the *h*-index to measure the quality of journals in the field of business and management. Information Processing and Management. 2012;48(2):234-41.
29. Soheili F, Khasseh A, Mousavi-Chelak A. The most influential researchers in information behavior. Aslib Journal of Information Management. 2017;69:215-29.
30. Negro A, Delaruelle Z, Ivanova TA, Khan S, Ornello R, Raffaelli B, et al. Headache and pregnancy: Asystematic review. The Journal of Headache and Pain. 2017;18(1):106.
31. Frazel JE. Optimize Migraine Management in Primary Care. The Nurse Practitioner. 2004;29(4):22-31.
32. Jay GW, Barkin RL. Primary Headache Disorders-Part 2: Tension-type headache and medication overuse headache. Disease-a-Month. 2017;63(12):342-67.
33. DeStefano D, Fuccella V, Vitale MP, Zaccarin S. The use of different data sources in the analysis of co-authorship networks and scientific performance. Social Networks. 2013;35(3):370-81.
34. Cugmas M, Ferligoj A, Kronegger L. Scientific Co-Authorship Networks. Advances in Network Clustering and Block modeling. 2019;363-87. doi: 10.1002/9781119483298.ch13
35. Cuellar M, Takeda H, Truex D. A methodological improvement in the evaluation of research output: An adapted use of the scholarly capital model. Twenty-fourth Americas Conference on Information Systems, New Orleans, 12 - 14 May Baltimore, MD. 2018.
36. Glanzel W, Schubert A. Double effort= double impact? A critical view at international co-authorship in chemistry. Scientometrics. 2001;50(2):199-214.
37. Stringer MJ. A complex systems approach to bibliometrics (doctoral dissertation). Northwestern University, Illinois, USA; 2009.
38. Hill VA. Collaboration in an academic setting: Does the network structure matter. Center for the Computational Analysis of Social and Organizational Systems (CASOS) Technical Report. 2008;1-19. Retrieved from www.casos.cs.cmu.edu/publications/papers/CMU-ISR-08-128.pdf.
39. Badar K, Hite JM, Badir YF. Examining the relationship of co-authorship network centrality and gender on academic research performance: The case of chemistry researchers in Pakistan. Scientometrics. 2013;94(2):755-75.
40. Sadatmoosavi A, Nooshinfard F, Hariri N, Esmaeil SM. Does the superior position of countries in co-authorship networks lead to their high citation performance? Malaysian Journal of Library and Information Science. 2018;23(1):51-65.
41. Yan E, Ding Y. Applying centrality measures to impact analysis: A co-authorship network analysis. Journal of the American Society for Information Science and Technology. 2009;60 (10):2107-18.
42. Kong X, Jiang H, Wang W, Bekele TM, Xu Z, Wang M. Exploring dynamic research interest and academic influence for scientific collaborator recommendation. Scientometrics. 2017;113(1):369-85.