Relationships between Scientific Collaboration Ego Network and Academic Influence: An Empirical Examination of Intelligence Science Scholar in China

Xiangjin Xiao¹ & Manoch Prompanyo²

¹ Ph. D. Candidate, Management, School of Management, Shinawatra University, Thailand
² Management, School of Management, Shinawatra University, Thailand

Correspondence: Xiangjin Xiao, Management, School of Management, Shinawatra University, Thailand.

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Abstract

In this study, the author collaboration network is established by taking the national social science fund papers in the field of intelligence science included in CSSCI as the data source and the paper collaboration relationship of high-yielding authors as the research object. The connection structure and influence of nodes in the network are analyzed by using the Ego-network analysis method, and the network size, intensity, density of high-yielding author ego-network and the relationship with the influence of academic influence of researchers are found out. Measures of academic influence were also validated analytically. The size of collaboration network and the strength of connection between network members of researchers are positively correlated with academic influence, and there is an inverted U-shaped relationship between network density and academic influence. Finally, this study proposes suggestions on how researchers can strengthen academic collaboration to enhance academic influence.

Keywords: academic influence, collaboration network, ego network, academic collaboration, intelligence science

1. Introduction

With the globalization of scientific and technological development, collaboration has become the mainstream mode of scientific research, and the collaboration relationship in scientific research is one of the important factors to improve the output ability of achievements (Zeyuan et al., 2005). Publishing papers is an important way to display scientific research results. For a long time, the National Social Science Foundation of China has strongly promoted the development of basic research in social science in China, and to some extent fund papers also represent the most advanced achievements in this field. The quantitative evaluation of the collaboration status of the authors of the social science fund paper led by intelligence science is helpful to reveal the current status and characteristics of the collaboration of research scholars in this field. How to realize scientific research collaboration and enhance its academic influence, most studies take macroscopic or mesoscopic perspectives, focus on scientific and technological management systems and policies and other themes, and there are relatively few studies from the microscopic perspective of researchers. The purpose of this study is to reveal the influence of collaboration on the performance of scientific research innovation from the perspective of Ego-network.

Many scholars are much concerned about the comparison of scientific research collaboration network characteristics in different disciplines. The usual research method is to construct a co-authorship network for empirical research by taking articles from a journal, a subject area, or a database as the research object. The pioneering results were the first to be published by M.E.J. Newman in Physica Review E in 2001, who carried out research on biology, physics, and computer science collaboration networks and laid the foundation in network static attribute statistics and network structure feature analysis (Zeyuan et al., 2005). Since then, some scholars have explored other disciplines, such as neuroscience, nanoscience, and high-energy physics in the field of natural science (Peter, 2002). Economics, library science, management science, tourism management science and many other disciplines in the field of social science (Yoshikane et al., 2006).

Whether the collaboration model between Chinese scientists has similarities with international collaboration, or whether they show their unique behavioral characteristics has become a concern for Chinese researchers. In the
past two years, there have been many empirical studies on scientific research collaboration networks, and the more concentrated studies are science, management and library and intelligence science (Liang et al., 2008). Empirical research mostly uses the overall network analysis method to carry out macroscopic statistical analysis of author collaboration network, basically from the aspects of centrality, agglomeration, shortest circuit, small world characteristics, scale-free characteristics, etc., which can only broadly point out the overall situation of collaboration between researchers within a discipline, and rarely observe the individual characteristics of the network.

Relying on the analysis method of Ego-network, this study attempts to describe the collaboration network structure of researchers in the field of intelligence science in China. By obtaining information about the network structure of individual relationship resources, the internal relationship between them and academic influence is explained. This will help this study to understand the connotation and efficiency of scientific research collaboration from a more microscopic level and provide support for promoting cooperative innovation.

2. Theory and Hypotheses

The academic collaboration network emphasizes the overall mode of connection between actors, and the focus of analysis lies in the characteristics of network connection and network structure, that is, the interaction strength of network connection, network density, and the location characteristics of individuals in the network, such as centrality, center and edge structure, connectivity, and other indicators. Among them, the interaction intensity and network density of social networks are closely related to the opportunities for scientific and technological personnel to realize scientific research collaboration (Liang et al., 2008). Moderately close network structure helps to reduce redundant information, accelerate the flow of information, make the acquisition of resources and information more convenient, and facilitate the improvement of internal innovation capacity of the network. The position of individuals in the social network has an important impact on their ability to acquire knowledge and skills. Individuals located on the key nodes of the social network structure can approach and occupy more network resources through their unique position in the network, discover more opportunities, and at the same time have more opportunities to contact new knowledge and new skills outside the network to achieve the improvement of academic influence. This study proposes the following hypotheses:

H1: The network size of Ego-network is positively correlated with academic influence;
H2: The network density of the Ego-network is positively correlated with academic influence;
H3: The strength of connection between network members of Ego-network is positively correlated with academic influence.

![Figure 1. Research conceptual framework](image)

3. Methodology

3.1 Data Source and Processing

3.1.1 Source and Processing of Data in Academic Collaboration Network

In the current generation method of individual center network members, most of them use the nomination generation method, and the respondents put forward the relationship characteristics of other members, which will artificially bring the high-density phenomenon of Ego-network due to questioning when collecting Ego-network data, and the subjectivity of the data masks the relationship of other members, thus affecting the quality of the data. The data collected in this study were obtained from the CSSCI database to reveal the relationship of scientific researchers from the perspective of co-published papers and to be able to get rid of the subjective bias of respondents during questionnaires.
The academic collaboration network is constructed based on the academic papers of scholars in the field of intelligence science, and the data sources of academic papers in the field of intelligence science used in this study are from CSSCI (China Social Science Citation Index Database). The search conditions were as follows: 1) The date of issuance from 2000 to 2020; 2) discipline type: library, information, and bibliography; 3) degree classification: library, information, and archives management; 4) fund category: national social science fund of China, and a total of 4,800 data were obtained (search time was June 27, 2021). By using bibliometrics and social network analysis, this study analyzes the collaboration network of high-yield authors, and discusses the main characteristics of scholars’ scientific research collaboration in the field of intelligence science in China.

After bibliometric analysis, there were a total of 4,800 papers in the discipline of intelligence science of the Social Science Fund from 2000 to 2020, with a total of 10,100 authors in the papers, 2.1 authors in each article, and a total of 4,306 authors in addition. The average number of articles per author was 1.11, indicating that many articles were completed by multiple authors in collaboration. All these basic attribute values indicate that cooperative publication is a common phenomenon in the field of intelligence science. Therefore, data in this field are suitable for research in scientific research collaboration networks. In order to construct a collaboration network matrix using the bibliometric software COOC for analysis in UCINET, this study selected 460 high-yielding authors who published more than 5 papers. In the scientific research collaboration network, the nodes are used to represent the scientific researchers, and the edges between the nodes indicate the paper collaboration relationship. Social network graphs were drawn using NetDraw integrated with UCINET 6.

3.1.2 Sources of Academic Influence Data

According to the fourth corporate social responsibility report released by Baidu in 2017, Baidu Academic has built a database of more than 4 million Chinese scholars, which is the largest Chinese scholar on the Internet and covers more than 95% of Chinese scholars (Baidu, 2021). This study plans to obtain the number of articles, frequency of citation, H-index, index, number of people concerned and other index data of scholars from the home page of scholars in Baidu Academic. A total of 458 scholars’ data in the field of high-yield informatics were collected, and 2 were missing.

3.2 Indicators of Scientific Research Collaboration Network

Social network analysis focuses on the set of social actors and their relationships, mainly answering questions related to social interactions. According to the starting point of analysis, social network analysis can be divided into two types: whole network and Ego-network (Jiade, 2005). The overall network refers to the network formed by the relationship between all members in a group, focusing on the structural characteristics of the overall network, and the quantitative indicators required are: density, centrality, agglomeration, etc. Ego-network is a network composed of one individual and multiple individuals related to it. Ego-network focuses on the “Ego.” Researchers measure the resource ownership of the Ego-network basically from indicators such as the size of the ego network (the number of network members) and the density of the network (the closeness of connections between network members). Meanwhile, because the position occupied by individuals in the network plays an important role in the acquisition of resources and information control, location metrics (especially central position and intermediary position) are particularly important.

By adding all the relationship matrices into UCINET6 software, this study obtained the network scale, density, and connection strength of the individual central network of 458 high-yielding authors. These three indicators were correlated and regressed with academic influence to verify whether there was a significant correlation between the degree of author collaboration and the academic influence of their scientific research output, and to infer whether strengthening scientific research collaboration could improve the academic influence of authors.

3.3 Measures of Academic Influence

Academic evaluation plays an important role in ecological academia (Yang et al., 2020). Peer review method is usually used for early academic evaluation, which is greatly affected by expert subjective factors, so a series of quantitative evaluation methods appear, such as the use of documents, citation frequency and other indicators to measure the academic influence of scholars from a single dimension. However, these single indicators do not comprehensively reflect the academic influence of authors (Feifei et al., 2020). Later, some researchers proposed comprehensive evaluation indicators, such as H-index (Hirsch, 2005), G-index (Egghe, 2006) And Page Rank based on citation link relationship construction (Egghe, 2006) And other indicators. Starting from the data availability, this study measures academic influence with multiple dimensions such as Total number of papers, Total number of citations, H-index, G-index, and Number of interested in scholars.

The number of papers refers to the number of all papers published by the scholar. The number of paper published
represents the ability of scholars’ output and is also an important embodiment of its academic influence. The frequency of citation refers to the sum of the frequency of citation of all papers published by a scholar. It is generally believed that the more papers are cited, indicating their value and influence, and representing the influence of the scholar.

The H-index is an indicator for evaluating academic strength in citation relationships, and proposed by Professor J.E. Hirsch, a physicist at the University of California, San Diego, USA, in 2005 to evaluate the personal performance of scientists. The H-index is defined as: a scientist’s score is \( h \), and only if no less than \( h \) citations are obtained per paper in the \( n \) papers, he/she published, and the number of citations per paper in the remaining \((n-h)\) papers of the scientist is less than \( h \) (Hirsch, 2005).

The G-index which is H-index derived index, is mainly proposed to compensate for the defects that the H-index cannot well respond to highly cited papers, and the G-index is defined as: the cumulative citation of papers relatively ranked in front after ranking by the number of citations is at least \( g^2 \). The maximum paper order \( g \), that is, the cumulative number of citations corresponding to the \((g + 1)\) order paper will be less than \((g + 1)^2\). From the definition, \( g \geq h \), while the number of citations of the top articles in order of citation, G-index.

In addition to the above indicators, this study also introduces the concept of network attention to evaluate the academic influence of scholars, that is, collecting the number of people interested in a scholar in Baidu Academic, the higher the number of people concerned, the stronger the influence of the scholar.

This study conducts factor analysis and confirmatory factor analysis on the above multiple measures to determine the optimal measurement model.

4. Data Analysis
4.1 Analysis of the Collaboration Network

The research object of this study is the author of the social science fund paper of intelligence science. The main purpose of scientific research collaboration network analysis is to use NETDRAW to map the collaboration network between these scholars, and then visually describe their collaboration status (Xia, 2006). To perform network analysis of scientific research collaboration, it is first necessary to import the author co-occurrence matrix into NETDRAW and map the knowledge (see Figure 2). The collaboration of the authors can be intuitively understood.

Figure 2. Collaboration Network Diagram
The network consists of 458 nodes and 1094 edges. The analysis of network components by Ucinet shows that the network is a non-connected graph with independent cooperative groups. A total of 111 components exists in the network, of which 81 independent nodes have no cooperative relationship with other members in the network; the largest component consists of 292 persons, accounting for 63.5% of the total number of nodes. There was one network component each with membership of 10, 7, 6, and 5, three with membership of 4, and four with membership of 3. The density of the whole network was 0.014 after density calculation. Degree describes how closely each node in the network graph is related to each other. Therefore, the network density is small and the connection between nodes is loose.

The average path length of this collaboration network was 7.418, indicating that 7.4 individuals had to pass between any two nodes to complete the information exchange. M.E.J.Newman of the University of Michigan, USA, had a statistical result of the average path length of 4.6, 5.9, and 9.7 for the data of large literature databases such as MEDLINE, losalamos e-Print Archive SPIRES, and NCSTRL between 1995 and 1999, respectively (M., 2003). The nodes of these datasets all reached more than 50,000, and relatively speaking, the small-scale collaboration network was constructed in this study, with a large average path length. The cohesion index based on distance was 0.070. This cohesion index is proportional to the cohesion of the overall network, and the magnitude of the values ranges from [0, 1]. Therefore, it can be judged that the cohesion of the overall network of cooperative social networks in the field of intelligence science is small.

4.2 Analysis of the Ego-Network

4.2.1 Analysis of Basic Indicators of Ego-Network

The analysis of the structure of Ego-network mainly starts with the connection strength, network density and size, and centrality of Ego-network. Using the Ucinet tool, the ego-network indicators that can be calculated include the size of the Ego-network, the total number of relationships (Ties), the maximum possible number of points (Pairs), the density (Density), the average distance (AvgDist), the diameter (Diameter), the number of weak components (nWeakComp), the ratio of the number of points in 2 steps to the size of the Ego-network (2StepReach), the efficiency (ReachEffic), and the middle person (Broker) (M., 2003).

Table 1 presents the network structure characteristic data of individual collaboration networks of the top ten high-yielding authors. First, in the network scale comparison, node X1 has the largest network scale (18), that is, it indicates that it has a cooperative relationship with 18 researchers; second, the largest density is X10 (40), indicating that he cooperates more with other collaborators in his Ego-network and interacts more frequently. In addition, the standardized intermediary (nEgoBe) value of X9 is 100, which can be said that its Ego-network internal knowledge exchange is smooth, and the concentration ability and control ability of knowledge are more prominent. Finally, because the total number of relationships (Ties) refers to the “total number of relationships between members of the Ego-network, excluding the relationship between each member and the “ego””, representing the closeness of collaboration between other members of the Ego-network, the highest value of Ties in this study was X1 (34), indicating that there were 34 collaboration relationships among its 18 members.

Table 1. List of basic indicators of Ego-network

|     | Size | Ties | Pairs | Densit | nWeakC | pWeakC | 2StepR | ReachE | Broker | nBroker | EgoBet | nEgoBe |
|-----|------|------|-------|--------|--------|--------|--------|--------|--------|---------|--------|--------|
| X1  | 18.000 | 34.000 | 306.000 | 11.110 | 5.000  | 27.780 | 10.240 | 56.630 | 136.000 | 0.440  | 124.000 | 81.050 |
| X2  | 5.500  | 2.000  | 20.000 | 10.000 | 4.000  | 80.000 | 1.310  | 75.000 | 9.000  | 0.450  | 9.000  | 90.000 |
| X3  | 7.000  | 4.000  | 42.000 | 9.520  | 5.000  | 71.430 | 4.140  | 76.000 | 19.000 | 0.450  | 19.000 | 90.480 |
| X4  | 10.000 | 10.000 | 90.000 | 11.110 | 5.000  | 50.000 | 5.660  | 65.000 | 40.000 | 0.440  | 38.000 | 84.440 |
| X5  | 5.000  | 2.000  | 20.000 | 10.000 | 4.000  | 80.000 | 3.270  | 88.240 | 9.000  | 0.450  | 9.000  | 90.000 |
| X6  | 8.000  | 10.000 | 56.000 | 17.860 | 4.000  | 50.000 | 7.840  | 72.000 | 23.000 | 0.410  | 21.500 | 76.790 |
| X7  | 10.000 | 12.000 | 90.000 | 13.330 | 4.000  | 40.000 | 3.270  | 55.560 | 39.000 | 0.430  | 37.000 | 82.220 |
| X8  | 1.000  | 0.000  | 0.000  | 1.000  | 1.000  | 100.000| 0.650  | 100.000| 0.000  | 0.000  |        |        |
| X9  | 5.000  | 0.000  | 20.000 | 0.000  | 5.000  | 100.000| 1.960  | 100.000| 1.000  | 0.500  | 10.000 | 100.000|
| X10 | 6.000  | 12.000 | 30.000 | 40.000 | 2.000  | 33.330 | 2.610  | 46.150 | 9.000  | 0.300  | 7.330  | 48.890 |

4.2.2 Network Location Analysis

Previous studies have shown that researchers who occupy a central position, usually also have high mediating centrality, tend to act as mediators of outward connections by their collaborators. Here this study uses Honest Broker Indices for discrimination. From the table, node X1 acts as an intermediary 25 times, and a total of 153
pairs of relationships are contacted, of which 136 pairs are purely intermediary (HBI0) relationships, that is, there is no direct connection between any two people contacted by the intermediary, and HBI1 indicates weak mediation, that is, a directed relationship is allowed between any two people contacted by the intermediary. HBI2 represents non-brokerage, that is, there is a two-way relationship between any two people contacted by the middleman (Jiade, 2005). On this basis, it is possible to deduce the importance of the role that experts, as intermediaries, play in their respective Ego-networks. The pure intermediary ratio shows that the node plays an intermediary role, because if this node is lost, the relationship between the people he contacts no longer exists.

Table 2. List of Honest Broker Indices

| Size | Pairs | HBI0 | HBI1 | HBI2 | nHBI0 | nHBI1 | nHBI2 |
|------|-------|------|------|------|-------|-------|-------|
| X1   | 18.000| 153.000| 136.000| 0.000| 17.000| 0.000| 0.000 |
| X2   | 5.000 | 10.000 | 9.000 | 0.000| 1.000 | 0.000| 0.000 |
| X3   | 7.000 | 21.000 | 19.000| 0.000| 2.000 | 0.000| 0.000 |
| X4   | 10.000| 45.000 | 40.000| 0.000| 5.000 | 0.000| 0.000 |
| X5   | 5.000 | 10.000 | 9.000 | 0.000| 1.000 | 0.000| 0.000 |
| X6   | 8.000 | 28.000 | 23.000| 0.000| 5.000 | 0.000| 0.000 |
| X7   | 10.000| 45.000 | 39.000| 0.000| 6.000 | 0.000| 0.000 |
| X8   | 1.000 | 0.000  |      |     |       |       |       |
| X9   | 5.000 | 10.000 | 10.000| 0.000| 0.000 | 1.000| 0.000 |
| X10  | 6.000 | 15.000 | 9.000 | 0.000| 6.000 | 0.000| 0.000 |

4.2.3 Analysis of Ties

The main index used to measure the strength of collaboration relationship in co-authorship networks is the eigenvector centrality, which not only considers the centrality of a node itself, but also considers the centrality of adjacent nodes, and believes that they can promote and enhance each other, which compensates for the lack of degree centrality (Jiade, 2005). If a node relates to a node with high centrality, the centrality of this node will also be improved. In other words, people associated with authorities, usually also more authoritative. On the contrary, one author and many cooperators have collaboration, that is, the dot centrality is relatively high, but if these cooperators are not authoritative scholars, the feature vector centrality of this author will not necessarily be relatively high.

Table 3. List of Bonacich Eigenvector Centrality

|        | Eigenvec | nEigenvec |        | Eigenvec | nEigenvec |
|--------|----------|-----------|--------|----------|-----------|
| X1     | 0.003    | 0.451     | X6     | 0.001    | 0.073     |
| X2     | 0.000    | 0.000     | X7     | 0.000    | 0.000     |
| X3     | 0.000    | 0.005     | X8     | 0.000    | 0.000     |
| X4     | 0.073    | 10.270    | X9     | 0.000    | 0.000     |
| X5     | 0.000    | 0.003     | X10    | 0.007    | 0.939     |

Comparing the feature vector and point-degree centrality of the top ten high-yielding authors, the highest feature vector value is X4 (0.073). Combined with numerical analysis and network location analysis, the members of the expert Ego-network with higher eigenvector centrality are more closely related to each other, and there is either a direct collaboration relationship between experts, or a collaboration connection is constructed through an intermediary. The high number of documents is also a close connection between researchers with a high amount of collaboration. If an author has collaboration with a well-known scholar, then this author will usually be more well-known.

4.3 Analysis of Academic Influence Measures

This study reviews the investigation of academic influence includes five observation indicators, namely, the number of documents issued, the frequency of citation, the H index, the G index, and the attention. Descriptive statistical analysis of the five measures showed that none of them were normally distributed, and in order to further improve the normality of the data distribution of the entire sample, natural logarithmic transformation of these five variables was conducted in this study. After transformation, except that the kurtosis value of hindex is
slightly greater than 5 (5.96), the kurtosis values of 4 variables are much less than 5, and the deviations are less than 3, basically meeting the criteria for normal distribution. See Table 4.

|                 | Mean | S.D.  | Skew  | Kurtosis |
|-----------------|------|-------|-------|----------|
| Papers          | 1.8675 | 0.48393 | -0.289 | 2.355    |
| HIndex          | 1.1878 | 0.31052 | 0.238  | 5.968    |
| GIndex          | 1.4256 | 0.30117 | -0.455 | 2.036    |
| Citation        | 1.9804 | 0.6749 | 0.828  | 1.772    |
| Concerned       | 2.9865 | 0.55092 | -0.353 | 1.219    |

The KMO test was conducted before factor analysis, and the KMO coefficient was 0.852, with a Bartlett’s test value of p < 0.001, indicating that this measurement index can be used for factor analysis. According to the correlation analysis between the indicators, except that Papers was not significantly correlated with other indicators, the correlation of other indicators was significant. Through factor analysis, the synthesis of a factor for each index can explain 84.1% of the variable error.

Therefore, in this study, the following two confirmatory factor analysis models were used to test the measure of academic influence:

Model I (CFA1): Five measurement variables combine into one latent variable, namely academic influence.

Model II (CFA2): The remaining four variables after eliminating the Papers indicator variable were combined into one latent variable.

The statistical fit indices of the two models were measured as shown in Table 5:

| Model | df  | $\chi^2$ | p     | RMSEA | NFI  | TLI  | CFI  |
|-------|-----|----------|-------|-------|------|------|------|
| CFA1  | 5   | 175.56   | .000  | .273  | .938 | .819 | .940 |
| CFA2  | 2   | 16.3     | .000  | .052  | .992 | .964 | .993 |

Comparing the two models of CFA1 and CFA2, the difference was significant ($\Delta \chi^2 = 159.26$), and the fit index of CFA2 was much better than that of CFA1, and all indicators reached the standard value, which indicated that the CFA2 model fitted very well.

It can be seen from Table 5 that the four measures of academic influence are not completely independent, but
tend to be a whole. It can be seen from Figure 3 that the factor loadings of the four measures of academic influence in the latent variable academic influence are relatively high (all close to 1), indicating that they can effectively represent academic influence. Therefore, this study will adopt the new variables synthesized by these four indicators to represent academic influence in the subsequent analysis.

4.4 Correlation Analysis

It is usually necessary to investigate the correlation of variables first to reveal the strength of statistical relationship between variables and provide the basis for further depicting and reflecting the quantitative change relationship between variables. Correlation analysis refers to the analysis of the degree of correlation between two variables. The relationship between two variables can be clarified by correlation analysis, which is usually expressed by Pearson correlation coefficient. This study analyzed all variables by correlation analysis. As shown in Table 6, the correlation between the various variables can be seen.

Table 6. Correlation matrix of variables

|       | Size   | Ties    | Density | DenXDen | AI      |
|-------|--------|---------|---------|---------|---------|
| Size  | 1      |         |         |         |         |
| Ties  | 0.641* | 1       |         |         |         |
| Density| 0.148**| 0.326**| 1       |         |         |
| DenXDen| -0.005 | 0.177**| 0.964**| 1       |         |
| AI    | 0.360**| 0.359**| -0.55   | -0.081*| 1       |

Through the data in Table 6, the scale and intermediary strength of the high-yield author cooperative individual network studied in this study are positively correlated with academic influence; the network density is significantly correlated with academic influence. This study attempts to analyze the data relationship between the quadratic term of Ego-network density and academic influence. As shown in Table 4, the quadratic term of network code is significantly correlated with academic influence.

In addition, it is generally believed that collinearity problems may exist if the correlation coefficient is above 0.75. In the study, only 0.641 had the highest correlation coefficient in the correlation analysis of variables, and it can be preliminarily judged that there is no problem of collinearity between variables.

4.5 Regression Analysis

This study preliminarily tested the relationship between network scale, strength and density and academic influence. Through regression model, the relationship between network scale, strength and density and academic influence, network scale and connection strength have a positive role in promoting academic influence. However, like the results of correlation analysis, the relationship between network density and academic influence was not significant. This study further examined the relationship between the quadratic term of network density and academic influence, and as shown in Table 7, the quadratic term of network density negatively affected academic influence, that is, the network density showed an “inverted U-shaped” relationship with academic influence.

Table 7. Results of regression analysis

|                      | Model 1 | Model 2 | Model 3 | Model 4 |
|----------------------|---------|---------|---------|---------|
| constant             | 67.030  | 114.617 | 302.143 | 280.543 |
| Size                 | 187.956 | 103.653 | 43.160  | 91.380  |
| (0.000)              | (0.016) | (0.011) |         | (0.044) |
| Ties                 | 58.044  | 89.705  | 96.013  |         |
| (0.017)              | (0.000) | (0.002) |         |         |
| Density              |         | -5.351  |         |         |
| (0.297)              |         |         |         |         |
| DenXDen              | -0.047* |         |         |         |
| (0.012)              |         |         |         |         |
| $R^2$                | 0.141   | 0.158   | 0.186   | 0.173   |
| $\Delta R^2$         | 0.141   | 0.014   | 0.028   | 0.015   |
| $\Delta F$           | 57.872* | 5.800*  | 11.854* | 6.505*  |

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The main reason for the inverted U-shaped relationship between network density and academic influence is that although maintaining a certain network density can enhance the trust degree between collaborators, so that the communication is smoother and the information transmission is more accurate. When the aggregation is close to a certain extent, it will lead to more redundant information and repeated knowledge, and it is difficult to obtain fresh and rich information and knowledge. Besides, it continues to improve the “network density” inside the small group to reduce the scientific research output. For researchers, only by breaking through the “small circle” and conveniently obtaining new knowledge from other groups and research fields can the vitality of scientific research be ensured and academic influence be improved.

5. Conclusion and Outlook

Although scholars recognize the importance of scientific research collaboration for academic influence, fewer scholars have empirically studied the relationship between the two from the perspective of Ego-network. Moreover, there is also an inconsistent understanding of exactly what impact scientific research collaboration has on academic influence. Through the collection of objective data, this study finds that the different characteristics of the Ego-network have different effects on academic influence. The main conclusions of this study are as follows: Firstly, network scale is positively correlated with academic influence. The scale of Ego-network represents the number of relationships cooperated by researchers, that is, in scientific research activities, if the network can actively produce collaborative relationships with others, it has more opportunities for knowledge sharing and exchange with other researchers, easy to realize knowledge innovation, and thus bring about an improvement in the efficiency of scientific research output. Therefore, the conclusions of this study validate previous studies by other scholars (Chunjuan et al., 2008). Scientific research collaboration has a positive effect on improving academic influence, so researchers and relevant management departments need to pay attention to the important role of scientific research collaboration and actively use scientific research collaboration to improve innovation performance.

Secondly, the connection strength of scientific research collaboration networks has a promoting effect on academic influence. The closeness of collaboration between other members of researchers in the Ego-network will promote the expansion of their academic influence. The more frequent the collaboration between members and the deeper the collaboration, indicating that the more frequent and in-depth the exchange between members is, which is conducive to the dissemination and diffusion of knowledge, and then has a positive impact on the academic influence of individual scholars.

Thirdly, there is an inverted U-shaped relationship between the density of the Ego-network and its academic influence. This shows that in scientific research activities, cooperators should avoid being limited to the “small collaboration circle” as far as possible, the network density of the collaboration network is high, and the lower the performance of scientific research output. The main reason is that if the internal members of the network are somewhat too consistent in the exchange, it will produce the phenomenon of “collective blindness”, which affects the output performance.

6. Limitations

This study uses the social network analysis method to analyze the author’s collaboration network from the ego-network level. Although there are some findings, this study still has following shortcomings: First, the sample size selected in this study is limited, only the author collaboration constructed by the Social Science Fund paper of Intelligence Science is collected, the network is only aimed at high-yield authors, and it does not reflect the author collaboration in this field very completely. Future studies can be conducted with a larger number of subjects and samples to enhance the robustness of the study conclusions. Second, the measurement of academic influence in this study is only calculated for the data of Baidu Scholars Database. The mathematical statistics done in this study are very large, while the number of on-site interviews is very small, which leads to the inability of the authors to deeply understand some characteristics in the process of paper collaboration to a certain extent. Hopefully, people can have a more detailed understanding of the law of paper collaboration in the field of scientific research by improving the above shortcomings.

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