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Bibliometric Analysis of the Global Trend in Centrality Measures

Mohd Fariduddin Mukhtar[1], Siti Haryanti Hairol Anuar[2], Zuraida Abal Abas[3], Mohamed Saiful Firdaus Hussin[1], Sahimel Azwal Sulaiman[4]
[1]Faculty of Mechanical Technology and Engineering, Universiti Teknikal Malaysia Melaka, [2]Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, [3]Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, [4]FCentre for Mathematical Sciences, Universiti Malaysia Pahang Al-Sultan Abdullah
Corresponding Author Email: fariduddin@utem.edu.my

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Abstract
Centrality is an essential concept in network sciences, which evolved from graph theory. The use of centrality measures allows the identification of the dominant elements in a network. The definition of centrality and the first associated interventions were developed for social network analysis and have since been applied to other fields. However, as the number of publications has steadily increased over the years, it is becoming increasingly difficult to maintain the growing volume of scholarly publications. Research and publications are extensively developed and have no proper record. Therefore, this study executes a bibliometric analysis on centrality measures, as well as its popular method: Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, and Degree Centrality, by reviewing a database that makes its research, awareness, global evolution, and potential trend lines available. Data were obtained from the Scopus database arranging from 2014 to 2024. The bibliometric analysis provides a valuable overview of the evolution of centrality measures in terms of the number of publications, most cited publications, most significant collaboration countries, and current trends in centrality. This study of bibliometric analysis on centrality measures have not been carried out yet. Therefore, prediction on the hotspots and current trends within certain research areas and methods would give researchers insight into further its development.
Keywords: Centrality Measures, Bibliometrics, Social Network

Introduction

Centrality measures are one of the vital tools for understanding the network model. It is a tool that provides an indicator to identify the most significant vertices in graph theory and network analysis. Among the applications of centrality, the analysis identifies the most influential people in a social network, identifying central web infrastructure nodes or urban networks, identifying disease spreader, and identifying brain networks. The concepts of centrality were first developed in social network analysis, and many of the terms used to quantify centrality based on the purpose of their sociological origin.

There are tremendous research and development as well as academic publications with regards to centrality measurement (Fariduddin Mukhtar et al., 2023). This certainly pose an increasing difficulty in keeping up with the influx of publications in this specific topic especially when conducting scientific research. In general, researchers constantly review and analyze previous studies to find new insights. As a matter of facts, different approach of reviewing and categorizing findings is adopted towards the increasing number and types of published documents. With the rising number of published documents, it is undeniable that researcher will be in misery if classifying the intended document is conducted without proper planning.

Regarding proper planning in conducting scientific research, bibliometric analysis was introduced to integrate knowledge and understand the evolution and trends in specific research. Bibliometric research terms were used to look at the number of publications, category of publications, a leading journal, writers, authors, organizations, and countries. Through detailed discovery and exploration in the evolution, growth, and trend of a specific body of knowledge or domain, a better and deeper understanding of the subject will be obtained and a guide for future research (Mukhtar et al., 2022). This paper aims to assist other researchers in this discovery and exploration, specifically in the domain of centrality measure in network or graph analysis through bibliometric analysis.

Therefore, this paper has two main objectives: (1) finding trends in research directions in centrality measures, (2) Perform a novel analysis on the feasibility and usefulness of centrality interventions in different fields using the data collected. The work heavily reviews the centrality world's intellectual structure by analyzing a database that allows its analysis, knowledge, global evolution, and future trend lines about centrality measures.

In this paper, section 2.0 presented a brief literature review on bibliometric and centrality, and section 3.0 presented the methodology used in this work. Section 4.0 presents results and discussion on the Bibliometric analysis towards centrality measurement body of knowledge. Finally, section 5.0 concludes the detailed work. It is hoped that this work will be a platform to guide researchers on the current and future research in network’s centrality measurement.

Literature Review

Centrality Measures

A graph is a diagram that depicts the relationships between objects which consists of vertices and edges. The strength of the connection or the weighted edges between the vertices can be depicted in this representation. Graph analysis, which employs graph theory containing vertices and edges, represents the entire system in a global system. The mathematician Euler solved the graph's idea of moving from town to city using seven bridges in 1736 for Urban Planning in Konigsberg, Germany (Ameer et al., 2019).

Since that time, graph has been widely used for replicated problems analysing data entries connected. For applications involving complex, unpredictable data, a graph can model both data features and their relationships concurrently compared to a conventional statistical method, which assumes that data are distributed independently and equally. Network sciences also able to model and analyse large-scale problems (Hassani et al., 2020). It gives researchers an efficient algorithm to find a meaningful pattern. There is four principal primary analysis in the graph model: community detection, connectivity analysis, path analysis and centrality analysis. Depending on the result needed, a different graph analysis algorithm can be applied to the network intended.

Centrality is one of the fundamental concepts in identifying essential nodes in a graph in which it is used to measure the importance (or "centrality," as in how "central" a node is in the graph) of various nodes in a graph. Until now, many measurements in centrality were discussed. Those measurements were the extension of four primary central measuring techniques, namely Betweenness Centrality (BC), Closeness Centrality (CC), Eigenvector Centrality (EC), and Degree Centrality (DC). The next subtopic will discuss these measures consisting of a brief introduction and an example for each of them using the widely used Zachary Karate-Club dataset (Hamilton et al., 2017) by implementing the algorithm for each method obtained from (Gómez, 2019). Zachary's karate club is one example of social relationships within a small group or organisation demonstrated in Figure 1.

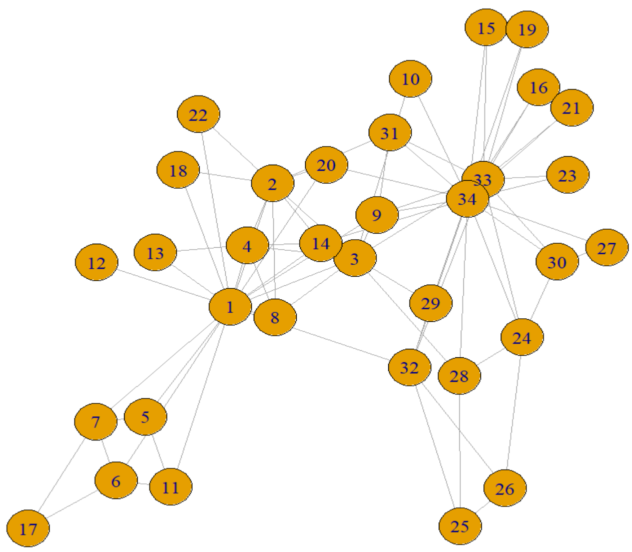
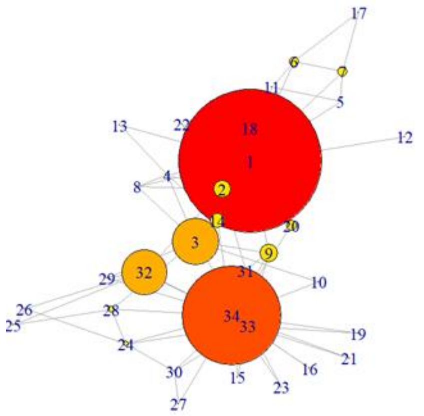


Figure 1: Zachary Karate Club Graph

Betweenness Centrality

Betweenness centrality (BC) is a well-known centrality measure used to capture a person's role in allowing data to flow from one network segment to the next. In particular, it determines how far a user is separated from other users in the network by the shortest path. The stronger a user's betweenness centrality becomes, the more people depend on them to connect with other people. The standard equation used to obtain the BC value, explain by equation (1) and illustrated in Figure 2. The sum represents the number of shortest paths from source node *s* to destination node *d*. σ_{sd} represents the number of shortest paths from source node *s* to destination node *d* and $\sigma_{sd}(i)$ is the number of those paths that include node *i* (Antiqueira & Zhao, 2014). In other words, the betweenness is the average fraction of trails that cross a node. For example, node 1 is the most influenced in the network, followed by nodes 34 and 33. Betweenness is zero (for node 17) if no tie or a present link is not part of any geodesic path.



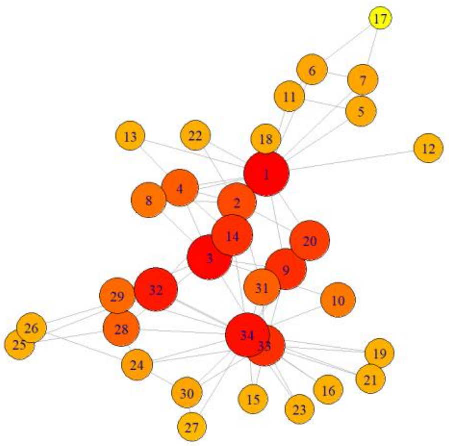
$$C_i^{(betw)} = \frac{1}{(N-1)(N-2)} \sum_{\substack{s.d=1 \\ s \neq d \neq i}}^{N} \frac{\sigma_{sd}(i)}{\sigma_{sd}}. \qquad (1)$$

$$|BC_1| = 231.07,\ |BC_{33}| = 76.69,$$
$$|BC_{34}| = 160.55,\ |BC_{17}| = 0.00$$

Figure 2: Betweenness Centrality

Closeness Centrality

The centrality of closeness (CC) indicates how close a node is to all other nodes in the network. It is computed by taking the mean of the shortest path lengths between each node in the network. The average distance between each vertex and every other vertex in the network is captured by CC, which measures each individual's position in the system from a different perspective than the other network metrics. Suppose vertices can only send messages to or influence their existing connections. In that case, a low closeness centrality indicates that a person is directly connected to or “just a hop away” from the majority of others in the network. The highest value in CC indicates a strong CC relationship among nodes and vice versa. Figure 3 illustrates the nodes involved in CC with the standard formula used. Nodes 1,33 and 34 dominates the CC, where they gave a similar and closes CC value as among the most decisive nodes in the network. Node 12 is closer to most nodes than node 17, which provided a value of 0.011 and 0.009, respectively.



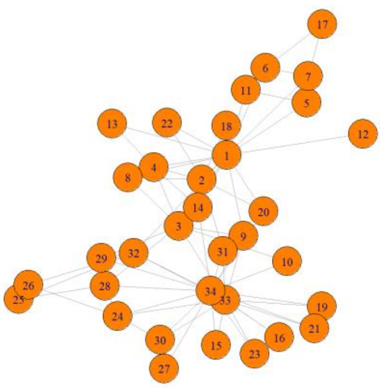
$$C_i^{(clos)} = \frac{1}{\sum_{j=1}^{N} d_{ij}} \qquad (2)$$

$$|CC_1| = 0.017,\ |CC_3| = 0.016,\ |CC_{34}| = 0.017,$$
$$|CC_{17}| = 0.009,\ |CC_{12}| = 0.011,$$

Figure 3: Closeness Centrality

Eigenvector Centrality

Eigenvector centrality (also known as eigen-centrality or prestige score) measures a node's influence in a network graph theory. All nodes in the network have been assigned relative scores based on the assumption that high-scoring nodes contribute more than equal connections to low-scoring nodes. A high eigenvector score indicates that a node is connected to many other nodes with high scores. An individual with few links could have a very high eigenvector centrality if those few connections were to very well-connected others. Because of eigenvector centrality, bonds may have a variable value, so connecting to specific vertices is more advantageous than relating to others. EC is illustrated in Figure 4, with its standard equation (3), the proportional constant. The a_{ji} term emphasises that node *i* receive the contribution to centrality from its neighbours through the incoming links. Node 34 has the highest EC value, indicating that he was the most influenced node in the network, followed by nodes 1 and 3. Node 17 gave a weight of 0.06 shows that he was the least affected nodes in the network.



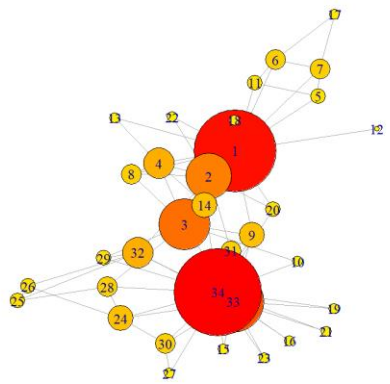
$$\lambda C_i^{(eig)} = \sum_{j=1}^{N} a_{ji} C_j^{(eig)} \tag{3}$$

$$|EC_1| = 0.95, \quad |EC_3| = 0.85,$$
$$|EC_{34}| = 1, \quad |EC_{17}| = 0.06,$$

Figure 4: Eigenvector Centrality

Degree Centrality

The degree centrality of a node is a simple count of the total number of connections to it. It's a kind of popularity metric. Still, it's a crude one that doesn't distinguish between quantity and quality. The value of the nodes' BC is the total number of edges that connect to it. There are two-degree measures for directed networks in degrees: the number of connections to a node, while out-degree is the number of links that begin at a node and extend to other vertices. Figure 5 shows the illustrations of DC given by equation (4), where k_i is the number of connections coming and going out from the nodes. Node 34 has the highest DC value, followed by node 1. While node 12 having only one path linking itself towards node 1.



$$C_i^{(\deg)} = k_i \quad (4)$$

$$|DC_1| = 16,\ |DC_{33}| = 12,\ |DC_{34}| = 17,$$
$$|DC_{12}| = 1,\ |DC_{13}| = 2,\ |DC_{15}| = 2$$

Figure 5: Degree Centrality

Bibliometric Analysis

Bibliometrics is a relatively new discipline of information science, helps gain insights into a research activity to identify hotspots and academically significant and landmark publications (Ben-daya et al., 2019; Glynatsi & Knight, 2021; Meo et al., 2021; Mumu et al., 2021; Saeed et al., 2021). Bibliometric analysis helps researchers and funding agencies focus more on under-investigated areas and make reasonable decisions related to the study. It is a method for using scientific instruments that is systematic, straightforward, reliable, and repeatable. Bibliometrics analysis techniques are more objective and dependable than other approaches. Large quantities of new data offer bibliometrics a valuable worldview by highlighting long-term patterns, identifying the most prolific and regular academics, and providing "the big picture of all study". Bibliometric analysis was previously described as statistical analysis to compile and summarise publication data (Xu et al., 2021). The obtained result cannot be viewed as a systematic answer to quality assessment. An article's number of citations does not inherently mean high quality but reflects its effect or usefulness (Hussin et al., 2021). Due to variations in the number of sources, direct comparisons between disciplines are difficult.

Bibliometric methods include using various tools to help researchers identify a specific and current research issue and determine its potential impact if it is carried out. The resources can help search for relevant scientific material, collect scientific data, and summarise the results. Knowing the evolution of the intended study area aids researchers in locating the most cited publications for references. On the other hand, the method would help locate a prestigious journal published in the study field (Meo et al., 2021).

According to our investigation, no research on the bibliometric analysis of the centrality measure has been conducted. Most of the document was based on the implementation of the measures. A bibliometric analysis of the centrality measure would shed light on the measure's growth and research pattern. The study's goal was to generate momentum for implementing centrality measures, particularly in the world of work.

Research Methodology

Figure 6 is a graphic representation of our bibliometric study outline. It is essential to get a proper grasp of the study's area or focus before anything else. The selection of keywords is vital because it highlights the themes and focus of the research content, indicating central focused areas that the researchers pursue and study. Keywords assist researchers in finding and retrieving relevant articles within scholarly databases index publications.

Regarding the scope of our research, we use only the “centrality measures” keyword Scopus database as the primary search engine because it is claimed to have the most comprehensive collections of scientific publications, books, theses, and journals. Sources for publication dates were restricted to those only published between 2014 and 2024. After having completed the data acquisition, the results were exported in BibTeX format and CSV. The maximum number of a dataset to be exported is just 2,000 per result causes us to extract the data by year. The dataset was inspected and then imported into a database in JabRef, where the spreadsheet was given descriptive value and expanded before being analysed in R. Bibliometrix package (biblioshiny) was then used in R software as research tools for evaluating bibliometrics and quantitative literature productivity (Aria & Cuccurullo, 2017). Biblioshiny package in R can easily be executed with the following instructions:

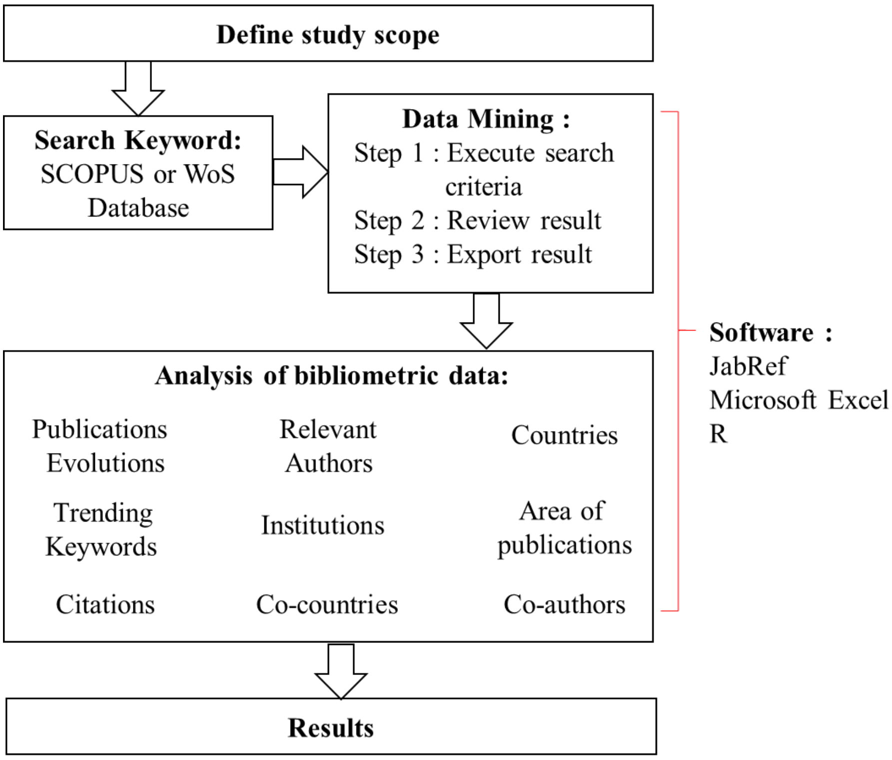


Figure 6: Bibliometric analysis framework

Results and Discussion

Centrality Measures Analysis

In the Scopus database, the filtering result based on the selected keyword "centrality measures" and limited to the only article with publication year ranging from 2014 – 2024, showing the following primary information as depicted in Table 1. From the table, there a total of 1498 article published in Scopus within the previous ten years, involving 4040 authors with an average of 14.99 citations per year. Based on the same filtering result, the trend of specific topics discussed over years reflected by the author keywords, is presented as in Figure 7. Among the specific topics under "centrality measures" filter results are the centrality measure metrics which had been predominantly used, such as betweenness centrality (BC), PageRank, eigenvector centrality (EC), closeness centrality (CC), and degree centrality (DC). Since this study explores and discovers the evolution, growth, and trend of centrality measure, only four centrality measure indicators are given focus for further analysis: BC, CC, EC, and DC measures. PageRank is an EC extension; hence it is regarded as an EC type (Boldi & Vigna, 2014).

Table 1
Main Information About the Collection Using Keyword "Centrality Measures".

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2014:2024
Sources (Journals, Books, etc)	765
Documents	1498
Average years from publication	4.38
Average citations per documents	14.99
Average citations per year per doc	2.315
References	58880
DOCUMENT TYPES	
article	1498
DOCUMENT CONTENTS	
Keywords Plus (ID)	6507
Author's Keywords (DE)	3624
AUTHORS	
Authors	4040
Author Appearances	5241
Authors of single-authored documents	108
Authors of multi-authored documents	3932
AUTHORS COLLABORATION	
Single-authored documents	118
Documents per Author	0.371
Authors per Document	2.69
Co-Authors per Documents	3.49
Collaboration Index	2.85

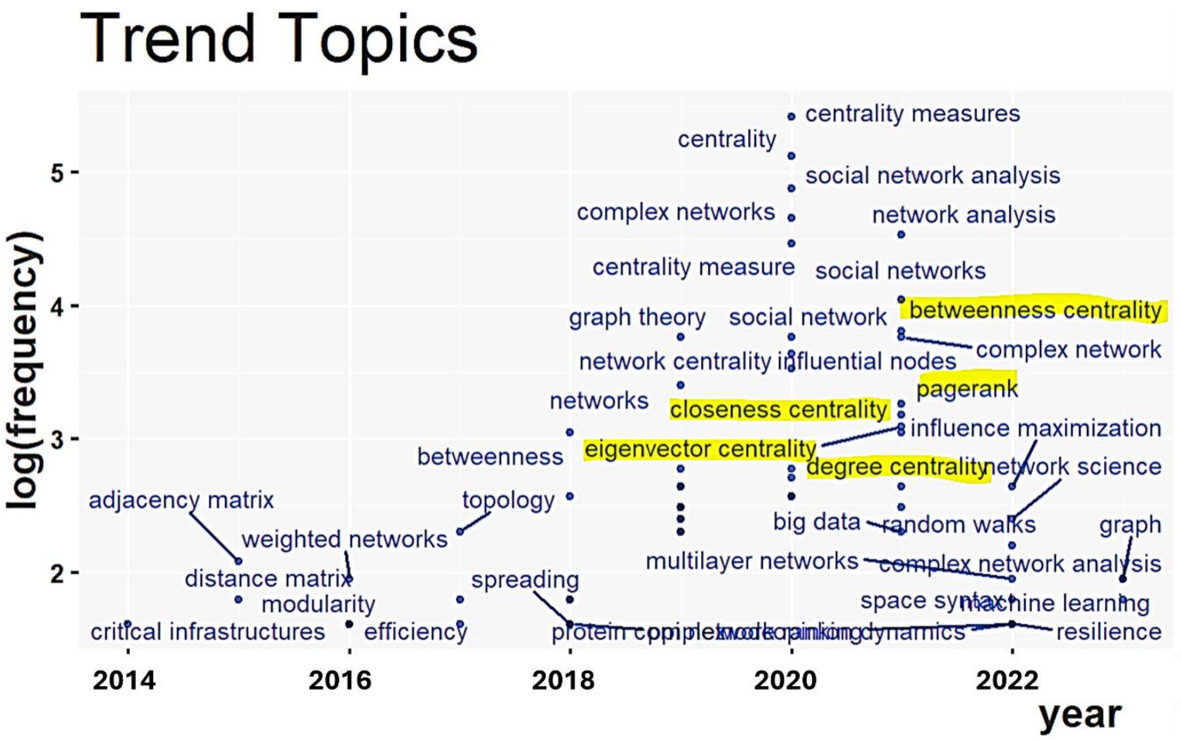


Figure 7: Trending topics discuss in centrality measures.

With the selected four trending topics discussed in centrality, further search query are extended to : (“Centrality Measures” OR “Betweenness Centrality” OR “Closeness Centrality” OR “Eigenvector Centrality” OR “Degree Centrality”) AND PUBYEAR>2013, PUBYEAR>2025. New results were obtained and exported as CSV and BibTeX types for both combined and each keyword, respectively. Ten popular author keywords and keywords-plus are shown in Table 2. Keyword-plus are words and sentences that appear in the authors' reference titles, which underlines emerging trends that briefly express the contents of articles. Keywords-plus shows are more descriptive analysis than assigned keywords by the author (Radhakrishnan et al., 2017).

The bibliometric analysis revealed that from the author keywords analysis, social network analysis, method of measurements used, and their interrelationship were among the dominant in author keywords analysis; while humans, brain, and nuclear magnetic resonance mapping were among the most frequently used keywords-plus. Results indicate that centrality measurement has been used in other areas, such as medical humanities and biochemical studies, while its importance in social network analysis cannot be overstated.

Figure 8 represents the co-occurrence of the author's keywords. It builds the network by considering each keyword to be a node and each coincidence of the two words to be a link. The frequency with which a few words coexist represents the strength of the connection between these two keywords. Furthermore, the Louvain algorithm was used to cluster nodes to estimate the density of connected nodes within the community. For example, the most popular author keyword, betweenness centrality, shared interest with closeness centrality and degree centrality in the same cluster, with a denser connection between them, indicating that there was work done among these three metrics of centrality measures. As a result, knowing the trending keyword in research would pique scholars' interest and attention.

Table 2
Top Ten Most Popular Author Keyword And Keyword-Plus

Author Keywords	**No of Articles**	**Keywords-Plus**	**No of Articles**
social network analysis	153	human	626
betweenness centrality	145	betweenness centrality	297
centrality	135	brain	291
complex networks	103	controlled study	274
centrality measures	95	complex networks	244
graph theory	88	brain mapping	212
network analysis	87	centrality measures	198
complex network	74	nuclear magnetic resonance imaging	162
social networks	68	magnetic resonance imaging	156
degree centrality	67	social networking (online)	156

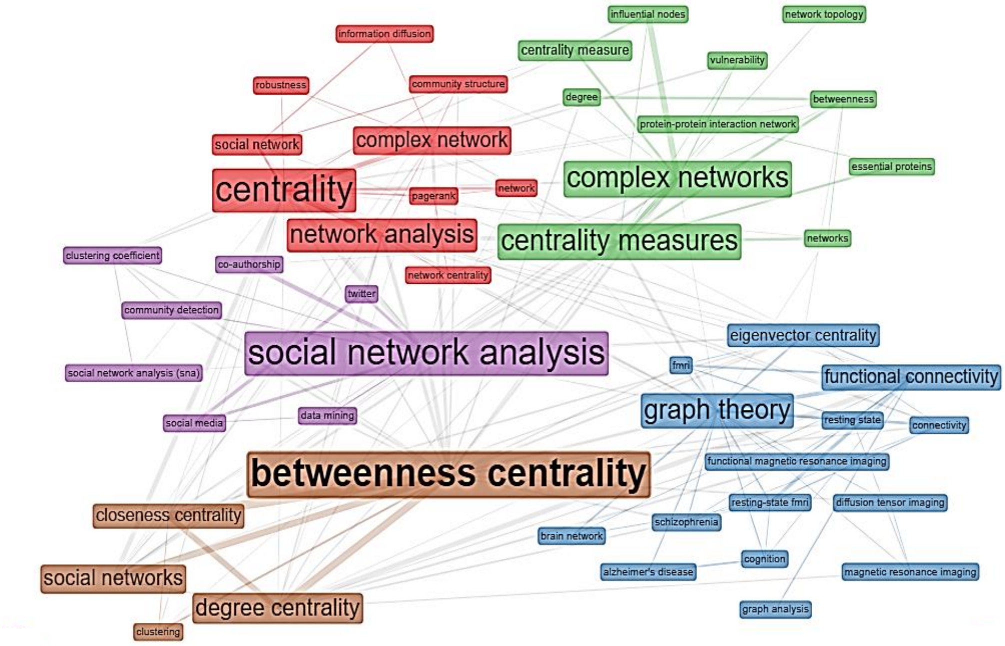


Figure 8: Trending keyword on centrality measure

Analysis of Publications

Growth of the Publication by Metrics

On publications analysis, we expand the result on centrality towards each method used. Output for each keyword was individually examined, and all combined keywords as shown in Table 3 and illustrated in Figure 9. Documents with all combined keywords indicate an increment of 67.818 yearly in publication. Regarding individual keyword selection, BC has garnered the most attention. BC experienced the most significant increase in contrast to other measures, increasing 25.53 yearly. The result indicates that researchers are mainly concentrated their efforts on BC advancement compared to other metrics. Other metrics also gain researchers' interest, as shown by the dotted trendlines. It can be seen that all the trendlines of the metrics positively increasing. The second highest publication increment is DC, followed by CC and EC with a rate of growth of (22.02), (12.19) and (9.61), respectively. Even though EC increased slowly, by 9.61 yearly increments, the substantial positive variation (0.9822) reflects that the method has the potential to keep growing.

Table 3
Number of Articles Published By Each Keyword From 2014 - 2024

Year	All	CM	BC	CC	EC	DC
2014	101	35	47	12	10	24
2015	140	47	67	14	10	26
2016	190	65	84	23	25	43
2017	236	85	113	39	34	52
2018	310	119	138	33	43	70
2019	384	134	151	59	49	100
2020	459	164	182	69	59	117
2021	489	166	227	83	70	115
2022	596	215	248	89	80	165
2023	648	211	242	110	101	182
2024	812	257	316	139	98	250
Total	4365	1498	1815	670	579	1144

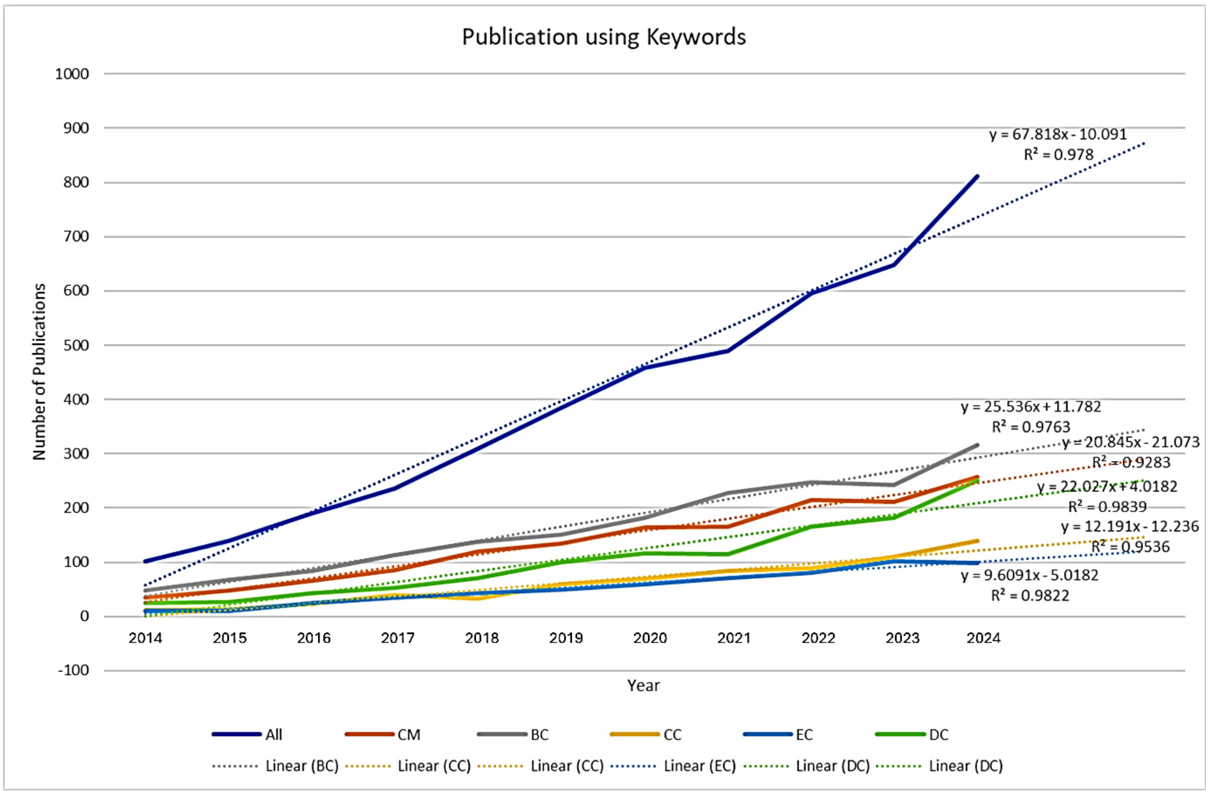


Figure 9: Publication analysis from keywords with trendlines

Growth of Publication by Combined Metrics

We also investigate whether the research involves combination of metrics and the mode of association results are shown in Figure 10. In general, the results show a positive increase in the number of publications for each combined method from 2014 to 2024. The tremendous increase is seen in publications that include both BC and CC in their articles, with an average increase of 32%. The same is true for BC and DC, which have average research growth of 27%. This implies that researchers are currently focused on the two methods in combination. On the other hand, the combination of the other metrics, such as BC and EC, is also favourable, with slow progression initially but showing the highest growth recently by 41%. However, other less explored method combinations can be investigated further with this insight. While other keywords show a slow progression in publications, the positive increase in the diagram cannot be denied, indicating the study's interest in the centrality measurement. It will be a valuable strategy for gaining access to less-explored knowledge about topics that have gotten more attention in the last decade. For example, another centrality measures, Decay Centrality applied on 46 real-world network problems to observe the relationships of the metric with DC and CC (Meghanathan, 2018) .

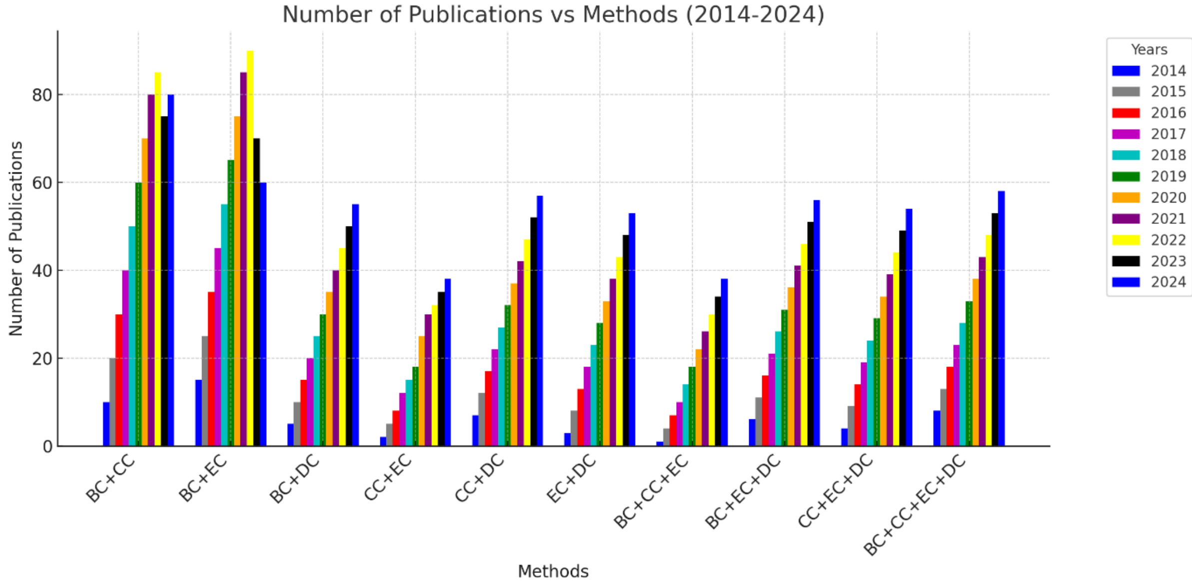


Figure 10: Growth chart by combined metrics

Most Published and Cited Journal

The top ten most-published and most-cited journals are shown in Table 4. The h-index is an author-level metric that assesses both researchers' productivity and the impact of their publications in terms of citations. The H-index reflects the content of the article in terms of its frequency of publication in this field. Results indicate that eight are also on the most-cited journal among those top ten most published journals. From this relationship, showing by the pointing arrows in Table 3, it can be seen that a well-known paper may help boost the citation rate of subsequent papers published in the journal (Lund & Maurya, 2020). For example, PLOS ONE is the leading figure as the most published and cited journal having 118 publications with 30 h-index citations. The publication in this prestigious journal would increase the journal's citation. This information would help researchers and academics find quality papers for references and publish them in quality journals.

Table 4
Relations on Top Ten Most Published and Cited Journal

Ranking	Most Published Journal (NP)	Most Cited Journal (H-index)
1	PLOS ONE (118)	PLOS ONE (30)
2	SCIENTIFIC REPORTS (80)	PHYSICA A: STATISTICAL MECHANICS AND ITS APPLICATIONS (24)
3	PHYSICA A: STATISTICAL MECHANICS AND ITS APPLICATIONS (64)	SCIENTIFIC REPORTS (18)
4	SCIENTOMETRICS (37)	PHYSICAL REVIEW E - STATISTICAL, NONLINEAR, AND SOFT MATTER PHYSICS (17)
5	PHYSICAL REVIEW E - STATISTICAL NONLINEAR AND SOFT MATTER PHYSICS (26)	NEUROIMAGE (14)
6	SOCIAL NETWORK ANALYSIS AND MINING (26)	SCIENTOMETRICS (13)
7	INTERNATIONAL JOURNAL OF MODERN PHYSICS C (22)	HUMAN BRAIN MAPPING (13)
8	NEUROIMAGE (19)	FRONTIERS IN HUMAN NEUROSCIENCE (10)
9	HUMAN BRAIN MAPPING (16)	INTERNATIONAL JOURNAL OF MODERN PHYSICS C (9)
10	PHYSICAL REVIEW E (16)	NEUROIMAGE: CLINICAL (9)

*NP: Number of Publications

Growth of Publication by Subject Area

Figure 11 depicts the top ten subject areas that are primarily utilising the centrality metrics. Each selected subject area is further classified into the percentage of the centrality method utilisation. According to the figure, Computer science is the leading one because centrality is a crucial concept in network sciences widely used. It must be noted that exploring the utilisation of the method in a specific subject area will assist researchers in further planning with regards to their strategy for knowledge advancement. One example would be exploring how best to use centrality measurement in the currently less discovered subject area such as business, management, and accounting.

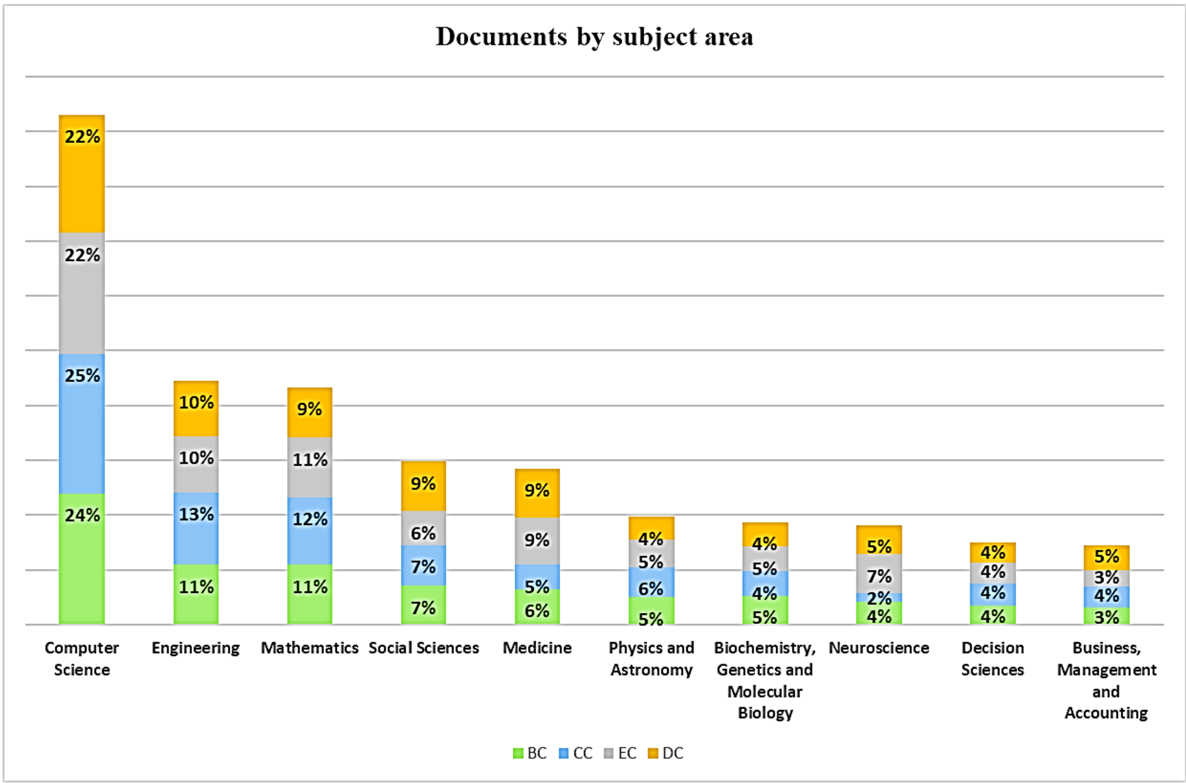


Figure 11: Top ten subject area using centrality

Growth of publication by region.

Table 5 shows the number of articles published by region. With 1502 publications, China is the most active country for BC, CC, and DC (36.6%). The United States is the most active country, with 1024 publications (25%) and most EC publications. Other countries that followed were South Korea, the United Kingdom, India, Germany, Italy, the Netherlands, Japan, and Spain, as shown in the table based on their ranked position in publications. On the other hand, Malaysia is ranked 19th in overall publication production, accounting for 0.9%.

The collaboration between countries on BC, CC, EC, and DC is depicted in Figure 12. It is a network comprised of nodes representing the authors' countries and links formed by co-authorships. The nodes' thickness indicates the degree of collaboration, while the nodes' scale indicates the total number of partnerships. The Louvain approach was used to cluster short enjoy a higher network density of connections. Clustering will aid researchers in identifying prosperous countries with which to collaborate. China and the United States of America (USA) collaborate the most. It is demonstrated by the thick borders between China and Hong Kong, the United States and Canada, the United States and Germany, the United States and the United Kingdom, and the United States and France.

Table 5
Country Keyword-Published Number of Articles

Rank	COUNTRY	BC	CC	EC	DC	TP (%)
1	China	642	239	134	487	1502 (36.6)
2	United States	429	154	175	266	1024 (25.0)
3	South Korea	116	38	31	86	271 (6.6)
4	United Kingdom	109	36	61	63	269 (6.6)
5	India	99	57	29	54	239 (5.8)
6	Germany	70	13	50	34	167 (4.1)
7	Italy	73	28	30	34	165 (4.0)
8	Netherlands	71	19	35	34	159 (3.9)
9	Japan	68	17	15	37	137 (3.3)
10	Spain	60	17	29	29	135 (3.3)
19	Malaysia	12	8	6	10	36 (0.9)

*TP: Total number of Publications

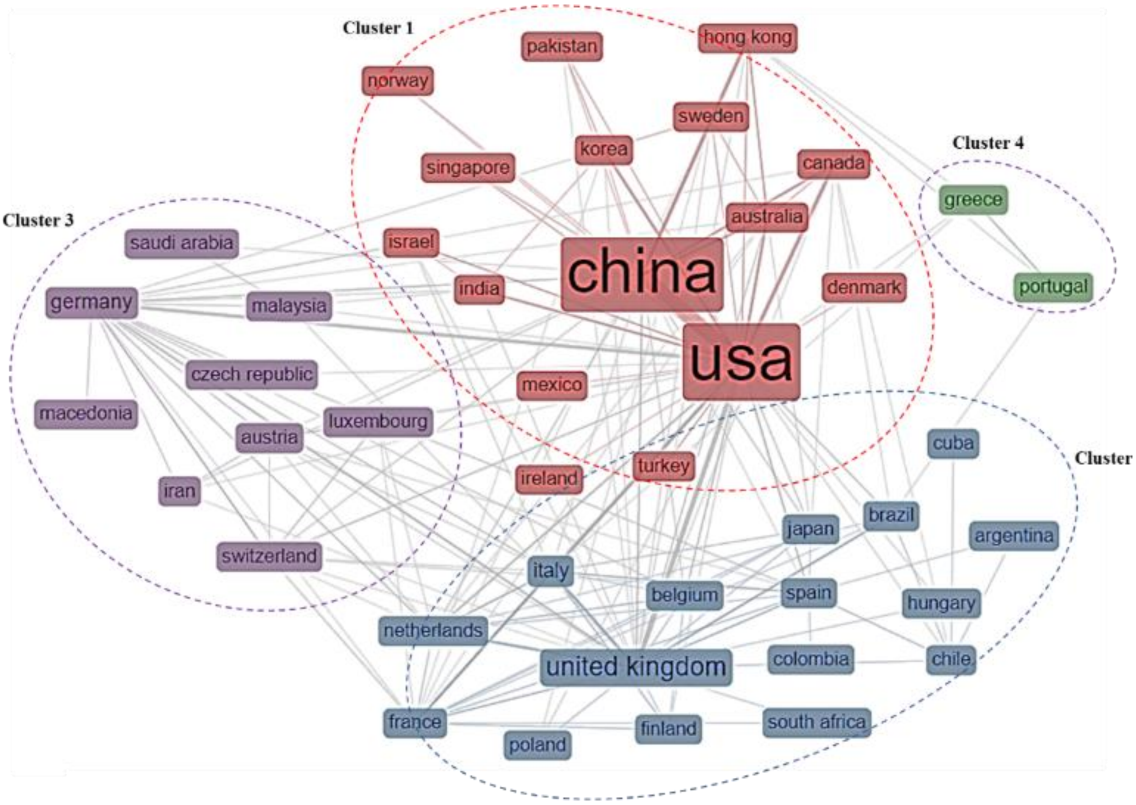


Figure 12: Collaborations of countries

Most Productive Authors

Table 6 displays the most productive author regarding the number of publications and h-index score for each method. Cornelis Jan Stam is BC's most prolific author, having published 12 times and receiving 9 h-index citations. Deng Yong is the most prolific CC researcher, with 7 publications and a 5 h-index. Arno Villringer has the most EC publications (15) and the highest h-index of any researcher (9). With 12 and 7, respectively, on the h-index, Hossain Liaquat have the most publications in DC.

Some writers also took part in other research metrics. Deng, Y., for example, participated in DC, CC, and BC. In EC, DC, and CC, the same is valid for Pan, Y and Li, M. Meghanathan, N., Hossain, L., and Wang, J. were among the authors who took part in DC and CC. In Figure 13, each author's participation in each method is visible. Having a thorough understanding of the specialised knowledge of the different approaches from productive authors gives researchers access to all their work and greater insight into their findings

Table 6
Top Ten Most Productive Author By Method

BC			**CC**			**EC**			**DC**		
Author	**NP**	**H-index**	**Author**	**NP**	**H-index**	**Author**	**NP**	**H-index**	**Author**	**NP**	**H-index**
Stam, C.J.	12	9	Deng, Y.	7	5	Villringer, A.	15	9	Hossain, L.	12	7
Jalili, M.	10	8	Li, M.	6	7	Mueller, K.	13	8	Shao, Y.	11	4
Ma, J.	10	6	Pan, Y.	6	7	Schroeter, M.L.	12	8	Deng, Y.	10	7
Lu, Z.M.	9	4	Chang, C.L.	5	3	Huang, P.	9	7	Uddin, S.	8	5
Deng, Y.	8	7	Meghanathan, N.	5	2	Wink, A.M.	9	7	Li, M.	7	12
Gao, X.	8	5	Wang, J.	5	9	Barkhof, F.	8	7	Pan, Y.	7	7
Hillebrand, A.	7	6	Crescenzi, P.	4	3	Zhang, M.	8	7	Wang, J.	7	14
Leemans, A.	7	7	Gao, C.	4	2	Jech, R.	7	5	Clemente, F.M.	6	4
An, H.	6	5	Hossain, L.	4	4	Li, M.	7	8	Huang, X.	6	2
Caeyenberghs, K.	6	5	Singh, S.	4	1	Pan, Y.	7	7	Meghanathan, N.	6	2

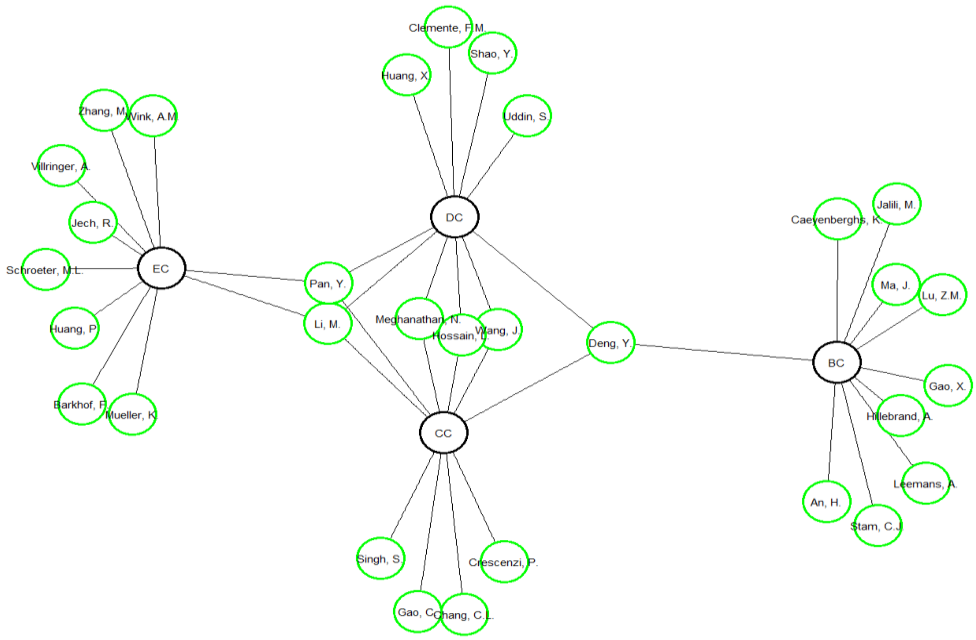


Figure 13: Participations of authors in centrality measures

Top Ten Most Cited Publications

Table 7 describes the top ten most cited publications on centrality in total citations and average citations per year from 2010 to 2020. Manlio De Domenico's article on multilayer networks, published in Physical Review X in 2014, was heavily cited in BC, DC, CC, and EC. Three of the top ten most cited articles were published in the Plos One journal, indicating that it is the most scholarly journal in networking, particularly in centrality.

Table 7
Most Cited Publications

Paper	Title / DOI	Total Citations	TC per Year
De Domenico M, 2014, Phys Rev X	Mathematical Formulation of Multilayer Networks 10.1103/PhysRevX.3.041022	547	68.375
Tang Y, 2015, Biosystems	CytoNCA: A cytoscape plugin for centrality analysis and evaluation of protein interaction networks 10.1016/j.biosystems.2014.11.005	336	48
Lohmann G, 2010, Plos One	Eigenvector Centrality Mapping for Analysing Connectivity Patterns in fMRI Data of the Human Brain 10.1371/journal.pone.0010232	281	23.4167
Kempe D, 2015, Theory Comput	Maximising the Spread of Influence through a Social Network 10.4086/toc.2015.v011a004	225	32.1429
Iyer S, 2013, Plos One	Attack Robustness and Centrality of Complex Networks 10.1371/journal.pone.0059613	221	24.5556
Gu J, 2013, Plos One	Use of Natural Products as Chemical Library for Drug Discovery and Network Pharmacology 10.1371/journal.pone.0062839	207	23
Boldi P, 2014, Internet Math	Axioms for Centrality 10.1080/15427951.2013.865686	191	23.875
Bae J, 2014, Phys A Stat Mech Appl	Identifying and ranking influential spreaders in complex networks by neighborhood coreness 10.1016/j.physa.2013.10.047	188	23.5
Pan Rk, 2011, Phys Rev E Stat Nonlinear Soft Matter Phys	Path lengths, correlations, and centrality in temporal networks 10.1103/PhysRevE.84.016105	180	16.3636
Riquelme F, 2016, Inf Process Manage	Measuring user influence on Twitter: A survey 10.1016/j.ipm.2016.04.003	173	28.8333

Figure 14 depicts the most relevant affiliations, with Capital Medical University leading the study, followed by the Chinese University of Electronic Science and Technology. Both are China's most prestigious universities. We can see that China's university controls seven of the top ten institutions in terms of affiliations. These findings back up previous research on the most influential sources and countries where China has conducted a recursive study in centrality measures.

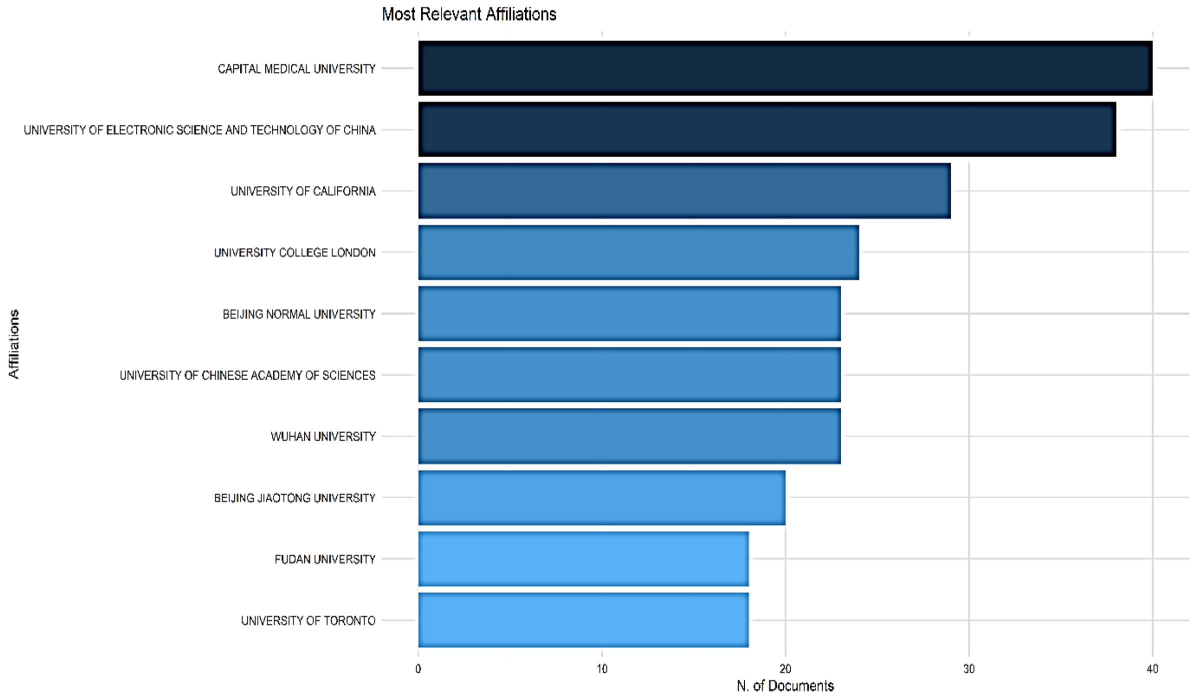


Figure 14: Top ten most relevant affiliations (institutions)

Current Trend in Centrality Measures

The advantage of Biblioshiny is the study of co-words between articles that show the global trend in thematic maps of publications. These maps are simple plots that enable us to analyse subjects based on their quadrant positioning: (1) upper right quadrant: motor topics; (2) bottom right quadrant: essential topics; (3) bottom-left: emerging or dissolving topics; and (4) top-left quadrant: highly skilled/niche topics. The thematic chart enables four different themes based on two dimensions: density and centrality, to be viewed. The current trend of centrality measures following 2020 and early 2021, shown in Figure 15. The most developed central measurement themes are the social networks and the significant role of the vector system. Other keywords instead indicate emerging or declining subjects, but they remain strongly positive. As a result, other topics continue to develop, and they are still at the beginning of 2021.

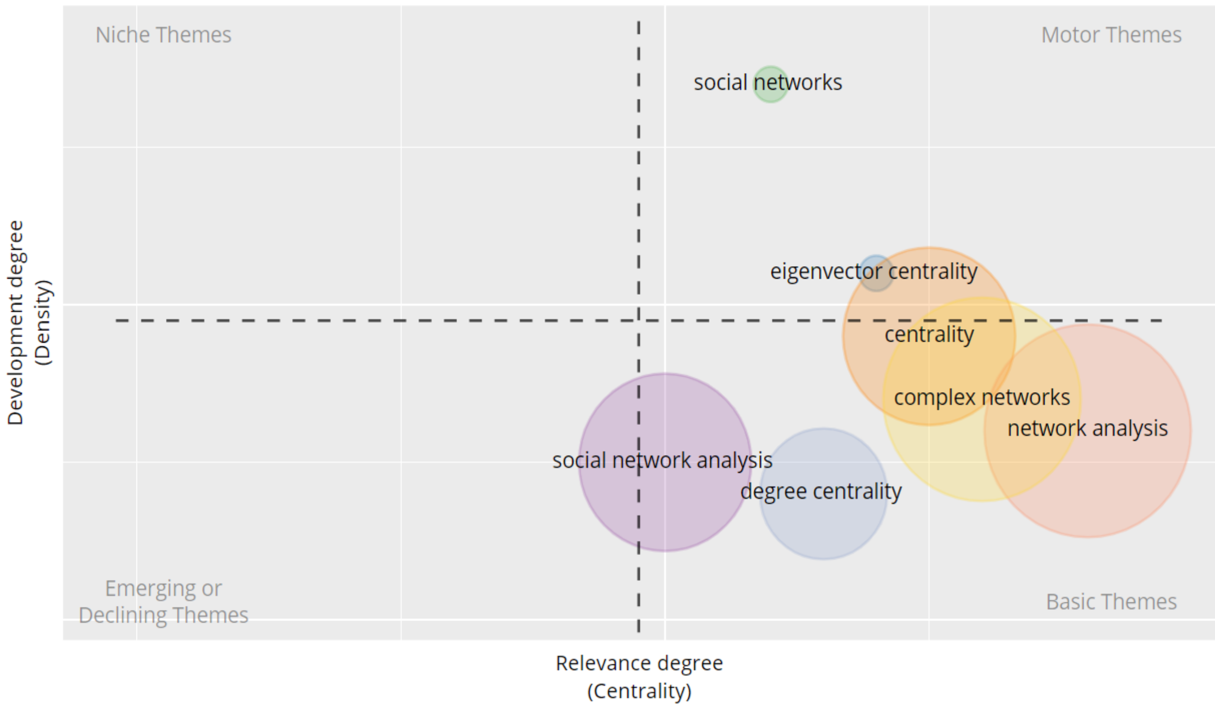


Figure 15: Thematic maps on trending keyword

Conclusions and Final Considerations

This study's main contribution is the identification of potential literature gaps for future research initiatives. This study's findings primarily include an extensive analysis of citation and co-citation structure and publication trends over time. Descriptive results were gathered and presented, elaborating on the attached figure to summarise significant research findings of centrality measures.

Using raw data from the Scopus database, publication characteristics such as quantity and quality were examined over ten years using a bibliometric analysis study. The study is the first to report global trends in centrality measures using its four well-known techniques: Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, and Degree Centrality. The following are the most apparent findings from this analysis:

i. A total of 4365 publications with the keywords “Centrality Measures” OR “Betweenness Centrality” OR “Closeness Centrality” OR “Eigenvector Centrality” OR “Degree Centrality” were found from 2010 to 2020.
ii. In terms of publication type, the article type emerges as the dominant category.
iii. Aside from centrality measures, other keywords (Betweenness Centrality, Closeness Centrality, Eigenvector Centrality and Degree Centrality) was chosen because it was a trending keyword and topic in the study area.
iv. According to the trendline analysis, BC is the most active centrality measure used by researchers, followed by DC, CC, and EC.
v. In publications, China and the United States dominate the centrality measure of development as the most productive and collaborative countries.
vi. Computer Science has the upper hand in the subject area in publications, accounting for more than 20% of all publications.
vii. Deng, Y., is the most involved researcher, taking part in DC, CC, and BC. Similarly, Pan, Y., and Li, M. are involved in EC, DC, and CC.

viii. Seven out of ten affiliations were from institutions in China, indicating the country's dominance in centrality.
ix. Current publication trends in 2020 show that social networks and eigenvector centrality are gaining traction among researchers.

Bibliometric analysis achieves its goals by focusing on the most prominent topics, publications, and trending themes in centrality measures. More in-depth and comprehensive research into each technique should be conducted recursively. Each discipline should research the applications of centrality in its domain. Combinations of several metrics should be considered to improve the development of centrality measures. Furthermore, it is expected that the number of studies relating to centrality will increase further over the next decade.

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