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THE CO-AUTHORSHIP NETWORK ANALYSIS OF RESEARCH PAPERS IN THE MALAYSIAN JOURNAL OF MATHEMATICAL SCIENCES IN 2019

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ABSTRACT

This paper examines the co-authorship network in the field of Mathematical Sciences, employing Social Network Analysis techniques to enhance understanding of research collaboration in this scientific community. This study applies the principles of network science, where authors are represented as nodes connected by edges based on co-authorship of papers. The co-authorship data from 68 articles published in the Malaysian Journal of Mathematical Sciences (MJMS) in 2019 is examined. The topology of 267 co-authorship networks published in MJMS in 2019 was explored using network analysis macro-level metrics to describe the clustering coefficient, density, network component, mean distance, and diameter. Also, micro-level metrics, such as degree centrality, closeness centrality, and betweenness centrality, were performed to measure the performance of each author and country in the network. Data analysis and visualisation were conducted using the Gephi tool. This study found that 10.29% of the papers were single-authored, while 89.71% were multi-authored. Notably, one author ranks highest in both degree centrality and betweenness centrality, indicating their pivotal role in connecting and collaborating with other authors and groups. Furthermore, Malaysia, Nigeria, and India played the most important roles in the co-authorship network.

2020 Mathematics Subject Classification:

INTRODUCTION

Co-authorship is one of the most recognisable forms of scholarly collaboration, serving as an indicator of scientific cooperation since the early 1980s. Collaborative research often leads to co-authorship, and this information is readily available in bibliometric data [15, 22]. It is generally assumed that researchers who collaborate will become co-authors when two or more people are listed as co-authors on the same publication [14]; conversely, it is implicitly assumed that all scientists who collaborate become co-authors when two or more people are listed as co-authors on the same publication. A co-authorship network is a social network consisting of scholars who are linked to one or more other researchers. Researchers communicate not just about their research activities, but also about how they cooperate to co-produce research and co-author research outcomes. This type of network consists of nodes (or vertices) that represent co-authors and edges (or links) that signify research acquaintance. An established set of mathematical tools, known as Social Network Analysis (SNA), is used to analyse and visualise the network [1,10,24].

Numerous studies have been conducted on the co-authorship network using SNA measures across various subject areas. For instance, Newman [16,17] explored co-authorship patterns by analysing entire bibliometric databases. Others have focused on fields such as chemistry, youth mentoring, information retrieval, library, and information systems to examine co-authorship patterns. However, all these studies were conducted outside of Malaysia. For instance, Di Bella *et al.* [7] analysed the scientific collaboration network at an Italian institute, while Yan *et al.* [25] mapped library and information systems in China. Given this context, this paper will focus on the co-authorship network in Malaysia.

In recent years, co-authorship networks, along with other types of networks, have been extensively studied to gain insights into the research landscape and its impact on research output [3]. Since the publication of de Solla Price's classic study on paper networks [6], bibliometric research has increasingly utilised network analysis. A co-authorship network connects two authors who have collaborated on a research publication. In its simplest form, a co-authorship network is formed when two authors (nodes) collaborate on an article (edge). Co-authorship networks provide a comprehensive and well-documented record of authors' social and professional connections. Analysing these networks can unveil various aspects, such as the level of fragmentation and cohesion of the knowledge community, or the identification of the most well-connected authors within the network [17]. The study of co-authorship networks also has been explored in various fields, such as tourism [2], medicine [26], and library and information science [25]. For the latest developments in co-authorship network analysis, readers can refer to [4, 11, 12, 13, 19, 20, 21].

Visualisation is a key component of network analysis, as it leverages humans' perceptual abilities to identify features in network structure and data. It adds meaning to the analysis, and the two complement each other. Many standalone SNA software products feature graphical user interfaces and do not require programming knowledge. Gephi and Ucinet are two popular examples of this type of tool. Gephi is an interactive visualisation and analysis software for networks, complex systems, dynamic and hierarchical graphs (Gephi). This tool facilitates the analysis and interpretation of graphs. It assists data analysts in making hypotheses, discovering patterns intuitively, and isolating structure singularities or defects during data sourcing. Visual thinking with interactive interfaces is increasingly recognised as a complementary tool to classical statistics, as it aids in reasoning and enhances the analytical process. Gephi delivers layout algorithms that are both efficient and of high quality. Its statistics and metrics framework includes commonly used metrics for SNA and scale-free networks [9].

SNA is a sociological method used to study the topological properties of networks. Its main objective is to gain a better understanding of a community by mapping the connections between individuals as a network and identifying key individuals, groupings within the network (components) and/or associations between them. In the context of SNA, nodes represent people, and links represent social connections between them, such as friendships, family ties, or financial relationships. SNA data can be analysed and interpreted in two main ways. Firstly, network metrics are used to characterise and quantify various dimensions of the network, including density, reciprocity, transitivity, centralisation, and modularity. Secondly, researchers can employ visual tools to study and interpret the structure of social networks.

Various software tools map the links between network players and generate social network graphs, sometimes known as “sociograms”. The colours in these graphs denote distinct types of actors or nodes on the graph. The node sizes represent the degree of connectivity. The placement and division of nodes in network maps indicate the network structure, including central actors, isolated actors, linking actors, and any sub-groupings or cliques. In this study, two categories are used for SNA, which are macro-level metrics and micro-level metrics. The macro-level metric describes the clustering coefficient, density, network component, and mean distance. Meanwhile, micro-level metrics analysed the nodes of the network using centrality measures.

The clustering coefficient shows how likely nodes with the same neighbour are to cluster together. The index has a value between zero and one. If the clustering coefficient is one, then the neighbourhood is completely connected; otherwise, the neighbourhood has no connection. The density measure is a ratio of the number of links in the network to the number of links, and it is always a value between zero and one. When one node is connected to the others by a direct connection or a series of connections, a group of nodes is defined as a network component [18]. The mean distance is measured between one node to another node based on the path in the network.

According to Freeman [10], which is still true now, “there is no unanimity on precisely what centrality is or on its conceptual basis, and there is minimal agreement on the correct process for measuring it”. The centrality measure consists of the degree of centrality, betweenness, and closeness. Degree centrality is the most straightforward method of determining the degree of a node in the graph. The degree of a node is just the number of additional nodes that are linked to the node. The degree of centrality may also be used to evaluate an actor’s communication activity or popularity. Another centrality measure is betweenness, which quantifies how far a specific node is separated from the network’s other nodes. Nodes with a high betweenness centrality play an important part in linking the network and the information flow and hence are a central node in the network [27]. Closeness centrality measures the average distance from one node to another. Freeman [8, 9] defined a node’s closeness as the “sum of reciprocal distance” between that node and any other node. Nodes with a high closeness score have the smallest distances between themselves and all other nodes. Closeness and betweenness centralities are path-based, showing a node’s relative position in the network. Closeness and betweenness centralities are path-based, reflecting a node’s relative location in the network, whereas a node’s degree shows the number of direct connections it has. Degree centrality and betweenness centrality are more commonly employed in SNA.

OBJECTIVES OF THE STUDY AND METHOD

This paper aims to conduct a co-authorship network analysis among authors of published papers in the Malaysian Journal of Mathematical Sciences (MJMS) in 2019. All the data is obtained from MJMS through the extraction of the bibliographic information. In total, this study includes data from 68 articles published in 2019. The bibliographic information of each article, such as the name of the authors, year published, title and country, was retrieved [23]. Then, those data are imported into a Microsoft Excel spreadsheet. Gephi, an open-source network analysis and visualisation software, was selected for the network visualisation and analysis of co-authorship in this study. To import the data into Gephi, it was necessary to create two files consisting of nodes and edges. The SNA method was used to characterise co-authorship networks at the macro- and micro-levels in t MJMS. Macro-level metrics focus on the topology aspects of a network as a whole to capture the overall structure of a network, whereas micro-level metrics focus on the evaluation of individual actors to capture each actor in a network [25].

Graph theory and networks: In this paper, graph theory is utilised to conduct SNA. Graph theory is the study of graphs, which are mathematical abstractions represented as nodes (also known as actors). Each pair of related nodes is connected by an edge (also referred to as a link or relation). A graph or network can be denoted as with node set and edge set. A simple graph is a graph with no loops and multiple edges.

This study takes into account four network macro-level features: Clustering coefficient, density, component, and mean distance, which are defined as follows:

Clustering coefficient: A clustering coefficient, also known as transitivity, is a measure of how closely nodes in a graph cluster together in graph theory. The formula to calculate the clustering coefficient C is:

$$C = \frac{3 \times \textit{number of triangle}}{\textit{number of connected triples}}$$

where the number of triangles represents node trios with each node connected to both others and connected triples represent node trios with at least one node connected to both others [17]. The index has a value between zero and one. The closer the value is to one, the higher the rates of the relationships among authors.

Density measure: Network density is defined as the number of edges in the network to the number of available edges, which is always a value between zero and one. The formula to evaluate the density for the directed graph is $D = \frac{m}{n\,(n\text{-}1)}$, where m is the number of edges and n is the number of nodes of the graph.

Component: A component is a set of nodes that can be reached by paths running along the edges of the network [5].

Mean distance: The mean distance between two nodes in a network is the mean length of the shortest path between them [25].

The micro-level features of the network are also applied: Degree centrality, betweenness centrality, and closeness centrality.

Degree centrality: The number of ties that a node has with other nodes in the network graph is equal to its degree centrality. This is the most straightforward method of determining the degree of a node in the graph. The following equation is used to calculate the degree of centrality:

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k)$$

where n is the number of nodes of the network. The distance function is $a(p_i, p_k) = 1$ if and only if nodes p_i and p_k are connected, and $a(p_i, p_k) = 1 = 0$ if otherwise [8]. Nodes with higher degrees indicate people who are likely to have the most knowledge or can easily link to a larger network.

Betweenness centrality: The number of shortest paths flowing through a node determines its betweenness centrality. Nodes having a high betweenness serve to connect various groups. The geodesic or shortest path is the path between two nodes that involves the fewest number of nodes in between and connects the two nodes. Let g_{jik} be the number of shortest paths linking nodes j and k, which pass through node i and g_{jk}, be the number of shortest paths between the nodes j and k. The betweenness centrality measure is given as follows:

$$C_B(v_i) = \sum_{j,k \neq i} \frac{g_{jik}}{g_{jk}}$$

where *i, j, k* = 1,2,3,...,*n*. Nodes with high betweenness are the brokers and connectors in social networks, bringing others together. Being between implies that a node can regulate the flow of knowledge between most others. Individuals with high betweenness serve as pivots in the flow of information networks. When the nodes with the greatest betweenness are removed, the average distance between others increases the most.

Closeness centrality: Closeness centrality is a metric that emphasises a node's distance from all other nodes in the network by focusing on the geodesic distance between each node and all others. Closeness is a measure of how long it will take for information to move from one node to another in the network. Closeness centrality is concerned with the extent of one's influence over the entire network. The following equation is used to calculate the centrality of closeness $C_c(n_i)$:

$$C_c(n_i) = \sum_{i=1}^{N} \frac{1}{d(n_i, n_j)}$$

where $d(n_i, n_k)$ is the distance between two nodes in the network.

RESULTS AND DISCUSSION

In this section, the visualisation and calculation in steps two and three are thoroughly examined. All the results will be presented in the form of a table, while the discussion to achieve the objective will be explained in detail. First, the micro and macro co-authorship networks of MJMS authors were analysed. The co-authorship network of authors is composed of nodes and edges, where nodes represent authors and edges represent co-authorship. A total of 68 articles from MJMS were examined in this study. A total of 176 authors contributed to the journal's articles in 2019. According to the analysis of all the articles, there were 7 articles (10.29%) contributed by single authors, 20 articles (29.41%) by two authors, 23 articles (33.82%) by three authors, nine articles (13.24%) by four authors, and nine articles (13.24%) by five or more authors.

In co-authorship analysis, network visualisations play a significant role in determining relevant relationships based on the distribution of authors and their specific connections in the network. All networks in this study were created using Gephi tools. The visualisations can be customised to display various appearances of the network by applying certain useful features, with numerous attributes to choose from based on the study. For example, Figure 1 illustrates the co-authorship network between nations using the Fruchterman Reingold layout in Gephi with no filters.

Figure 1: The co-authorship network between countries in MJMS

The clustering coefficient is visualised in Figure 2. The clustering coefficient of a node measures how close the node is to a graph cluster. The index has a value between zero and one. The bigger the size of nodes, the higher the rates of relationships among authors. The two largest blue nodes indicate authors with the highest rates of relationships with other authors, while the small black nodes represent authors with no connections (index 0) in the co-authorship network. The largest component, consisting of 26 vertices, represents 14.77% of all authors in the co-authorship network, as shown in Figure 3. Typically, the most prolific authors are located within the largest component, making it the central hub of productivity in the network. Highly productive authors have lower geodesic distances and shorter paths to other authors compared to less prolific authors.

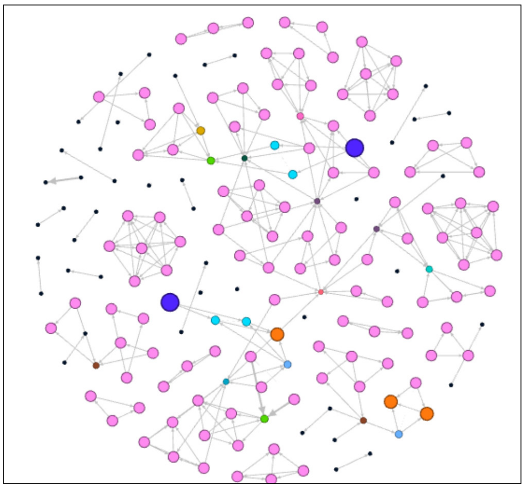


Figure 2: The clustering coefficient of the authors in MJMS

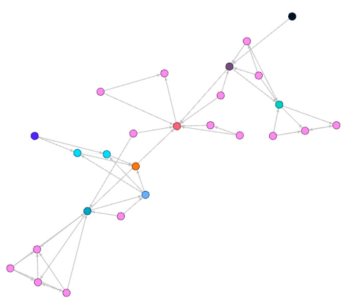


Figure 3: The largest component of the authors in MJMS

For the micro-level metrics, the nodes of the network were analysed using centrality measures (degree, betweenness, and closeness). Degree centrality is the most straightforward method of determining the degree of a node in the graph. The size and colour of the nodes correspond to the number of degrees. The greater the node's size, the greater its number of degrees. Aside from that, the colour of the nodes denotes their degree of centrality. Figure 4 depicts the degree centrality of the authors' co-authorship network, whereas Figure 5 depicts the co-authorship network of the nations in MJMS. The large black node denotes the node with a high degree of centrality and the small green nodes denote the node with the lowest degree of centrality.

For the collaboration between authors of different countries, the small blue node represents the node with the lowest degree of centrality, while the large pink node represents the node with the highest degree of centrality. The other nodes have an intermediate degree of centrality. A node's degree is just the number of extra nodes that are directly connected to it. The degree of centrality can also be used to evaluate an actor's communication activity or popularity.

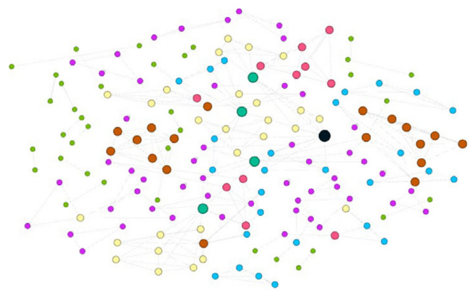


Figure 4: The degree centrality attribute of the authors in MJMS

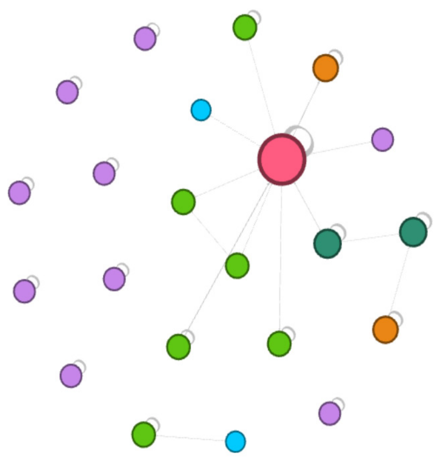


Figure 5: The degree centrality attribute of countries in MJM

The visualisation in Figure 6 represents the betweenness centrality attribute for authors, while Figure 7 shows the betweenness centrality attribute for countries. The largest nodes in blue indicate authors or countries with the highest betweenness centrality values, while the smallest nodes in light yellow represent those with the lowest betweenness centrality. The nodes in blue and the biggest size indicate the highest betweenness centrality, while the smallest nodes in light purple have low betweenness centrality. The nodes with medium sizes in orange and green have intermediate values of betweenness centrality. Betweenness centrality measures how central and well-connected a specific node is to other nodes in the network. The author or country with the highest betweenness centrality metric serves as a crucial connector within the network.

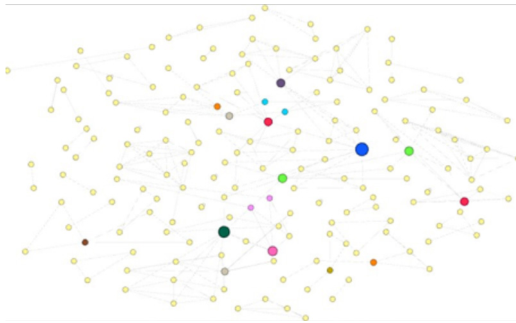


Figure 6: The betweenness attribute of authors in MJMS

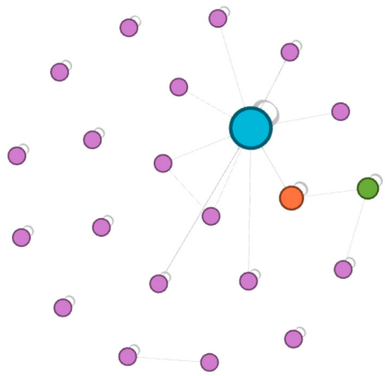
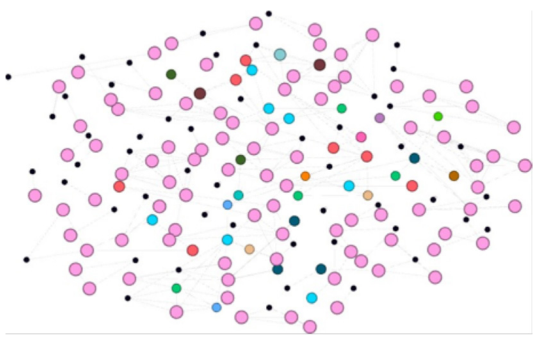


Figure 7: The betweenness attribute of countries in MJMS



Figures 8 and 9 show the closeness centrality attribute of the authors and countries in MJMS, respectively. The average distance between two nodes is measured by closeness centrality. The large pink nodes, up to 50% of them, represent authors with the highest closeness centrality values, while the small black nodes represent authors with the lowest closeness centrality values. Additionally, the three largest blue nodes indicate countries with higher closeness centrality values, while the smallest light purple nodes represent countries with the lowest closeness centrality values. Nodes with high closeness scores have the shortest distances to all other nodes in the network, making them well-connected and central within the network. Figure 8. The closeness centrality attribute of authors in MJMS.

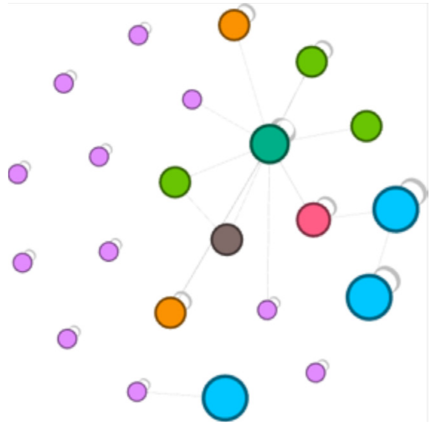


Figure 9: The closeness centrality attribute of countries in MJMS

To understand the concept of the co-authorship network in this study, each aspect is implemented accordingly. In the case of MJMS, an author is represented as a node, and an edge signifies a relationship between two authors when they have co-authored an article together. The journal consists of 176 authors and 267 co-authorships, resulting in a graph network with 176 nodes and 267 edges.

A macro-level metric describes the clustering coefficient, density, network component, mean distance and diameter. The clustering coefficient of a node measures how close the node is to a graph cluster. The total clustering coefficient for all nodes in the network is 0.355, indicating that the network is clustered. Another network topology attribute is the density. The density of the authors' co-authorship network in MJMS is 0.009, indicating that just 0.9% of all ties are present. In MJMS, the co-authorship network of authors consists of one main component and several discrete components. This network has 45 components, the largest of which accounts for 14.77% of the whole network. It indicates that a considerable number of authors are linked together in a cohesive network. In addition, the network contains seven isolation components of size 1. A total of seven authors have not collaborated with any of the others. According to the average shortest path, the average distance between authors in the network is 1.387, implying that most authors in the network are separated by less than two degrees. Furthermore, because the network diameter is 3, the farthest authors in the giant component of the network can be reached in three stages. The summary statistics for the authors' network are shown in Table 10.

Table 10: Summary statistics for authors' network in MJMS

Overview	Results
Nodes	176
Edges	267
Average degree	1.517
Network diameter	3
Graph density	0.009
Connected component	45
Average clustering coefficient	0.355

Isolated nodes	7
Size of main component	26 (14.77%)
Average path length	1.387

Table 11 shows the top 10 authors and their clustering coefficient. Figures 12, 13 and 14 show the co-authorship network in each network analysis. After extracting the co-authorship network in Gephi, the ranking has been assessed in the data table. Furthermore, the data table is sorted from higher to low values. The highest value for the clustering coefficient belongs to Mohamad, M. S. and Shah, M. M. showing that they have the highest rates of relationship with the authors.

Table 11: The top 10 authors and their clustering coefficient

Rank	**Name**	**Clustering Coefficient**
1	Mohamad, M. S	1
2	Shah, M. M	1
3	Mohamed, N. F	0.666667
4	Ng, T. S	0.666667
5	Mohamed, N. H	0.666667
6	Johnpillai, A. G	0.5
7	Hannache, A	0.5
8	Laouar, A	0.5
9	Tukhtasinov, M	0.5
10	Mustapokulov, K	0.5

Figure 12: The co-authorship network of the authors and the clustering coefficient

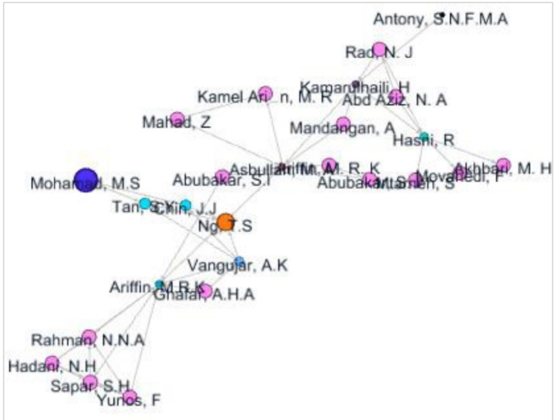


Figure 13: The co-authorship network of the authors in the giant component

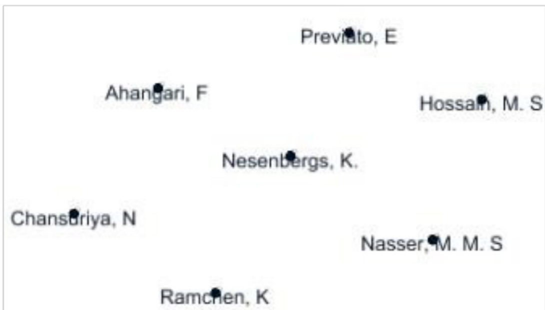


Figure 14: The co-authorship network of the isolated authors

Micro-level network analysis examines the characteristics and roles of individual authors and nations within the network. Using centrality metrics, the SNA method was also applied to investigate significant research collaborations to capture the characteristics of each participant in the network. Measures of centrality reveal the significance of an actor in a network (Benckendorff, 2010). Degree, closeness, and betweenness centrality were used to analyse the co-authorship network of nations in MJMS. Table 15 presents the top 10 authors for each of the three centrality metrics, while Figures 16, 17, and 18 display the network connections between those authors in the respective rankings.

Table 15: Centrality measures of authors in MJMS

	Degree Centrality		Betweenness Centrality		Closeness Centrality	
RANK	**Name**	**Frequency**	**Name**	**Frequency**	**Name**	**Frequency**
1	Ismail, F	10	Ismail, F	28	Mohamed, N. F	1
2	Ibrahim, Z. B	8	Ariffin, M.R. K	22	Johnpillai, A. G	1
3	Ariffin, M.R. K	8	Vangujar, A. K	15	Hannache, A	1
4	Bachok, N	8	Kamarulhaili, H	12	Laouar, A	1
5	Abdullah, M. A	8	Asbullah, M. A	12	Tukhtasinov, M	1

6	Ullah, K	6	Ibrahim, Z. B	11	Mustapokulov, K	1
7	Khan, B. A	6	Hasni, R	10	Bakar, H. S	1
8	Ozer, O	6	Bachok, N	10	Sapar, S. H	1
9	Nisar, Z	6	Ayub, A. F. M	6	Sani, M	1
10	Mohd Nor, S. R	6	Yusoff, B	6	Midi, H	1

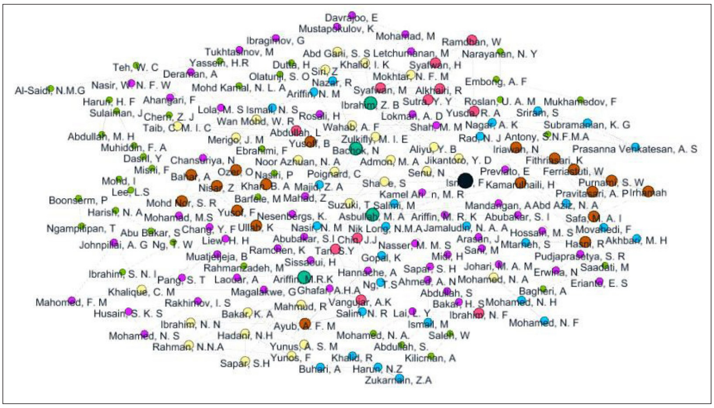


Figure 16: The network between authors and the ranking in degree centrality

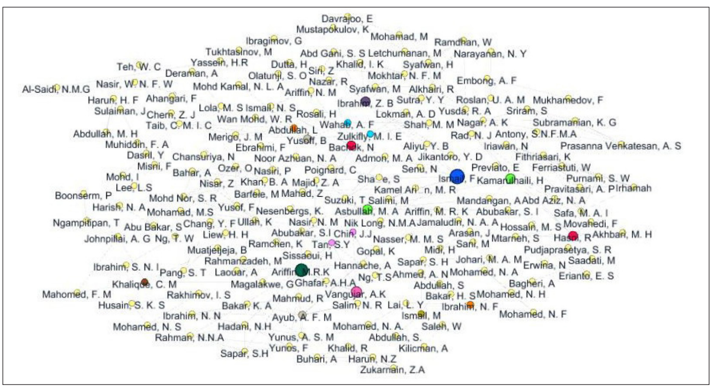


Figure 17: The network between authors and the ranking in betweenness centrality

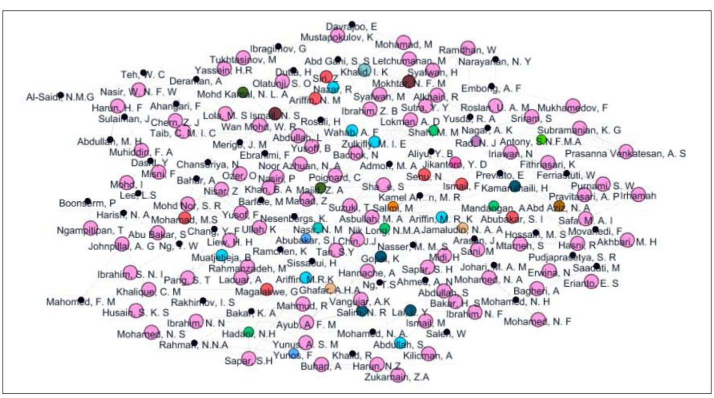


Figure 18: The network between authors and the ranking in closeness centrality

From the rankings above, Ismail, F. holds the first place in the ranking for degree centrality with a value of 10, indicating numerous collaborations with distinct authors in single articles. Ismail, F. also ranks first for betweenness centrality with a value of 28, signifying a central role in connecting and bridging other authors within various groups. As for closeness centrality, 88 authors share the first place with a value of 1 (see Appendix A). These authors are instrumental in efficiently disseminating knowledge to other authors without relying on intermediaries for collaboration. Table 19 presents the centrality rankings for all countries, and Figures 20, 21, and 22 display the network connections between those authors on three levels.

Table 19: Centrality measures between countries in MJMS

	Degree Centrality		Betweenness Centrality		Closeness Centrality	
RANK	**Country**	**Frequency**	**Country**	**Frequency**	**Country**	**Frequency**
1	Malaysia	16	Malaysia	55	India	1
2	Nigeria	5	Nigeria	14	United Kingdom	1
3	India	5	India	8	Sri Lanka	1
4	Iran	4	Iran	0	Malaysia	0.75
5	United Kingdom	4	United Kingdom	0	Nigeria	0.5625
6	South Africa	3	South Africa	0	France	0.473684
7	Uzbekistan	3	Uzbekistan	0	Uzbekistan	0.454545
8	France	3	France	0	Pakistan	0.454545
9	Japan	3	Japan	0	Iran	0.45
10	Pakistan	3	Pakistan	0	Japan	0.45
11	Australia	3	Australia	0	Germany	0.45
12	Algeria	2	Algeria	0	South Africa	0
13	Germany	2	Germany	0	Australia	0
14	Thailand	2	Thailand	0	Algeria	0
15	USA	2	USA	0	Thailand	0
16	Iraq	2	Iraq	0	USA	0
17	Indonesia	2	Indonesia	0	Iraq	0
18	Qatar	2	Qatar	0	Indonesia	0
19	Latvia	2	Latvia	0	Qatar	0
20	Bangladesh	2	Bangladesh	0	Latvia	0
21	Sri Lanka	2	Sri Lanka	0	Bangladesh	0
22	Saudi Arabia	1	Saudi Arabia	0	Saudi Arabia	0

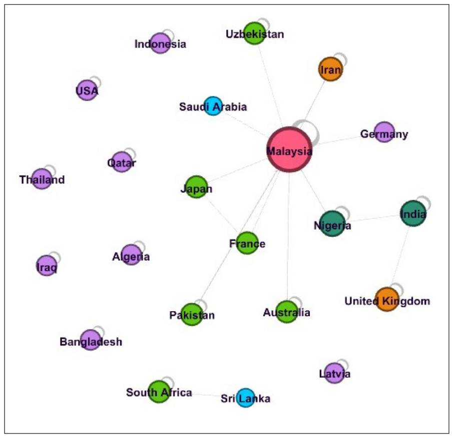


Figure 20: The network between countries and the ranking in degree centrality

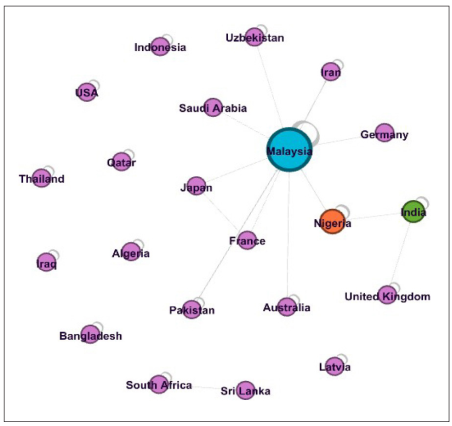


Figure 21: The network between countries and the ranking in betweenness centrality

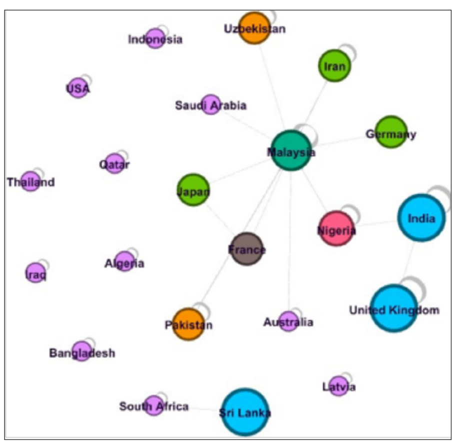


Figure 22: The network between countries and the ranking in closeness centrality

In terms of degree centrality, Malaysia (16), Nigeria (5), India (5), and Iran (4) are the most prolific nations. In this co-authorship network, Malaysia (55), Nigeria (14), and India (8) hold the highest betweenness centrality values, indicating their pivotal positions in the network as they connect multiple authors and potentially serve as the shortest paths between different countries. These countries play a crucial role in facilitating information distribution within the network. Moreover, India (1), The United Kingdom (1), and Sri Lanka (1) rank highest in terms of closeness centrality, underscoring their efficiency and essential role in swiftly disseminating information among the network nodes.

CONCLUSION AND FUTURE WORK

In this study, both macro and micro-level metrics of Social Network Analysis (SNA) were utilised. At the macro-level, measures such as clustering coefficient, density, network component, mean distance, and diameter were employed. At the micro-level, centrality measures, including degree centrality, betweenness centrality, and closeness centrality, were examined. A total of 68 articles from 176 authors published in MJMS in 2019 were manually collected. The data included the date of publication, authors' name and their country, as well as the title of the articles, and they were tabulated in Microsoft Excel. According to the analysis of all the articles, 10.29% of the articles were authored by a single author, while the rest were co-authored by multiple authors. After extracting and analysing the data in Gephi, the co-authorship network was visualised and examined. The network consists of 176 nodes representing authors and 267 edges representing co-authorship relationships. Macro-level analysis revealed that Mohamad, M. S. and Shah, M. M. have the highest rates of relationship with other authors based on their clustering coefficient, which has the highest value. The complete data can be found in Table 11, and the overall network visualisation was also presented. Based on a complete analysis of micro-level metrics, the rank of the authors and countries was based on their value in three centralities. The ranking demonstrates how connected and influential the authors are in the network. Ismail, F. was the only author who ranked in both degree centrality and betweenness centrality, indicating a high level of influence in the network compared with the others. Furthermore, Malaysia stood out as the most influential country contributing to the articles in MJMS.

Most existing research papers in the field focus only on micro-level metrics of SNA analysis, and only a few cover both macro and micro-level metrics. Additionally, these papers mainly concentrate on countries outside of Malaysia. Therefore, this study aims to address this gap by analysing the co-authorship network using both macro and micro-level metrics, focusing on data from MJMS, a Malaysian mathematical journal. While the co-authorship network in this research is relatively small, it provides valuable insights for future studies. To enhance the analysis, future research should consider extending the data collection period to at least five years to observe network changes over time. Moreover, incorporating additional indicators such as eigenvector centrality, PageRank centrality, and HITS could offer a more comprehensive assessment of authors' influence within the network.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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