



Mapping the Collaboration Network: A Co-Authorship Analysis of Major Statistical Journals in Nigeria (2020–2024)

***Bakle, Z.O., & Adeyeye, L.A.**

Department of Statistics, Federal College of Animal Health and Production Technology

*Corresponding author email: zenretbakle@gmail.com

Abstract

This research investigates the structure and dynamics of academic collaboration within Nigeria's statistical research community by conducting a social network analysis of co-authorship in three prominent journals: The Central Bank of Nigeria Journal of Applied Statistics, The Journal of the Nigerian Statistical Association, and The Journal of the Royal Statistical Society Nigeria Group. A total of 61 articles published between 2020 and 2024 were analysed. The data gathered included author names, institutional affiliations, and publication information. Using this data, a co-authorship network was created and evaluated through centrality measures (closeness, betweenness, and degree), along with indicators of network cohesion such as density, clustering, giant components, average path length, and diameter. Assortativity coefficients were calculated to examine the impact of institutional, regional, and organisational proximity on collaboration patterns. The results indicate a highly centralised network featuring a limited number of influential authors and a dominant giant component, pointing to uneven collaboration. High assortativity scores related to institutional and regional characteristics demonstrate a strong tendency for localised collaboration, whereas lower assortativity based on institution type suggests limited cross-organisational interaction. These findings reveal both the strengths and weaknesses in scholarly collaboration within Nigeria's statistical research community and provide insights for promoting more inclusive academic networks.

Keywords: Co-authorship Networks, Social Network Analysis, Statistical Journals, Institutional Assortativity, Regional Collaboration

Introduction

Research collaboration plays a crucial role in academia for a variety of reasons. It not only advances knowledge but also ensures that such progress translates into broader societal impact (Fari & Ingawa, 2020). As research problems grow in complexity and the value of knowledge continues to rise, collaboration becomes increasingly necessary. Through shared responsibilities and pooled expertise, collaboration enables more comprehensive, innovative, and impactful research outcomes. It helps prevent duplication of efforts (Fari & Ingawa, 2020), optimises resource use, and often leads to enhanced research productivity and visibility (Lewis et al., 2012). Additionally, the current academic landscape—shaped by globalisation, competitiveness, and institutional rankings—frequently rewards collaborative research (Mydin et al., 2021 & Lewis et al., 2012). Collaboration is also particularly beneficial for early-career academics. Working with experienced colleagues provides exposure to new techniques, improves research skills (such as grant writing and publication), and enhances overall academic competence (Mydin et al., 2021). Collaborative environments foster self-confidence, reduce isolation, and promote the development of essential soft skills like communication, teamwork, and project management (Mydin et al., 2021 & Lewis et al., 2012). Furthermore, research partnerships expand professional networks and increase visibility within the academic community (Abbas, 2016 & Lewis et al., 2012). A key representation of research collaboration is co-authorship networks—structures that connect researchers based on shared publications. These networks play an essential role in the dissemination of knowledge, acting as conduits for research findings, ideas, and expertise across academic communities (Network Effects Are Critical for Research Collaborations, n.d., & Biscaro & Giupponi, 2014). They also support critical analysis, interdisciplinary research, and deeper engagement

1 | Cite this article as:

Bakle, Z. O., & Adeyeye, L. A. (2025). Mapping the collaboration network: A co-authorship analysis of major statistical journals in Nigeria (2020–2024). *FNAS Journal of Mathematical and Statistical Computing*, 2(3), 1-15. <https://doi.org/10.63561/jmsc.v2i3.852>

with scholarly work (Afolabi et al., 2021, & Ullah et al., 2022). As such, the structure of co-authorship networks significantly shapes how knowledge is created, shared, and expanded (Sameer Kumar, 2015 & Carchiolo et al., 2022).

Co-authorship networks provide a helpful lens through which to understand the dynamics of academic collaboration. Social Network Analysis (SNA) offers a robust methodological framework for examining these networks, using various measures to map the relationships and interactions between authors (Moayednia et al., 2014 & Roslan et al., 2019). By representing authors as nodes and their co-authorships as edges, SNA enables a detailed examination of collaboration patterns and facilitates the identification of central figures, research clusters, and structural gaps (Roslan et al., 2019 & Fagan et al., 2018). These analyses can be performed at different scales, from micro-level assessments of individual influence (e.g., degree and betweenness centrality) to macro-level evaluations of entire networks (e.g., density, clustering, and community structure) (Moayednia et al., 2014 & Roslan et al., 2019). They also inform discussions on research performance, collaboration efficiency, and the evolution of academic communities over time (Newman, 2004; Roslan et al., 2019 & Sameer Kumar, 2015). Co-authorship network studies have been conducted across a broad range of disciplines, including the natural sciences (e.g., biology, medicine, mathematics), social sciences (e.g., economics, management, education), and technical fields (e.g., information systems and library science) (Afolabi et al., 2021, Roslan et al., 2019, Biscaro & Giupponi, 2014 & Almuhananna et al., 2022). These studies also span diverse geographic regions. Examples include Asia (e.g., China, India, Malaysia) and Europe (e.g., Italy), to the Americas (e.g., Brazil, Canada) [(Afolabi et al., 2021), (Moayednia et al., 2014, Roslan et al., 2019, Sameer Kumar, 2015, Carchiolo et al., 2022 & Morel et al., 2009)]. Despite this global scope, regional analyses remain essential for understanding local collaboration patterns. In Nigeria, co-authorship studies exist but are limited in scope and coverage. Few studies have conducted in-depth, cross-journal analyses of research collaboration in the statistical sciences. This gap presents a valuable opportunity for a more comprehensive investigation.

In this study, we examine co-authorship networks within three major Nigerian statistical journals: The CBN Journal of Applied Statistics, The Journal of the Nigerian Statistical Association, and The Journal of the Royal Statistical Society Nigeria Group over the period of 2020 to 2024. Drawing on 61 published papers involving 149 researchers, we employ Social Network Analysis to explore the structure of the co-authorship network, the extent of institutional and regional collaboration, and the formation of research clusters. We also assess how collaboration patterns vary across journals and institutions, and we identify the most influential contributors. Ultimately, this study provides insights into the nature and structure of research collaboration within the Nigerian statistical community and identifies areas where inter-institutional collaboration can be strengthened.

Specifically, this research aims to explore and understand the structure, dynamics, and patterns of research collaboration in the Nigerian statistical community. The specific objectives were to:

1. To construct and visualise the co-authorship network of researchers.
2. To examine patterns of collaboration.
3. To identify research clusters.
4. To identify influential researchers within the network.
5. To analyse the structure of the co-authorship network.

Methodology

Data Extraction

Co-authorship data were obtained from three key Nigerian statistical journals: the *Central Bank of Nigeria Journal of Applied Statistics*, the *Journal of the Nigerian Statistical Association*, and the *Journal of the Royal Statistical Society Nigeria Group*. A total of 61 papers published between 2020 and 2024 were collected for analysis.

From each paper, the following information was extracted: authors' names, year of publication, paper title, and affiliated institutions. Using institutional information, additional attributes were generated to classify each author by region and type of institution. The compiled data were saved as CSV files.

The Python pandas library was used for data cleaning and the creation of an edge list for the co-authorship network. An edge list includes any two authors who co-authored a paper. Two files were created: the edge list and an author attribute file.

Data Analysis

Social Network Analysis (SNA) was conducted to explore the structural characteristics of the co-authorship network in the selected Nigerian statistical journals from 2020 to 2024.

The network was constructed using the igraph library in R, while network visualisations were generated with ggnetwork. The following network properties and characteristics were analysed:

A. Graph Construction

- **Simple Graph:** The network was reduced to a simple graph by removing self-loops (edges connecting a node to itself) and collapsing multiple edges between the same pair of nodes into a single edge.

B. Centrality Measures (Vertex Characterisation)

To identify influential authors in the network, three centrality measures were computed and used to rank authors:

- **Closeness Centrality:** This measures how close a node is to all other nodes in the network. It is defined as the inverse of the sum of the shortest distances from the node to all others:

$$c_{CI}(v) = \frac{1}{\sum_{u \in V} \text{dist}(v, u)},$$

Where $\text{dist}(v, u)$ is the length of the shortest path(s) between the vertices $u, v \in V$.

- **Betweenness Centrality:** This measures how often a node lies on the shortest paths between other nodes, reflecting its role as a bridge in the network:

$$c_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s, t | v)}{\sigma(s, t)},$$

where $\sigma(s, t|v)$ is the total number of shortest paths between s and t that pass through v , and $\sigma(s, t)$ is the total number of shortest paths between s and t (regardless of whether or not they pass through v).

- Degree** **Centrality:**
 This indicates how many direct connections a node has:

$$c_{dg}(v) = \frac{deg(i)}{N-1}$$

where $deg(i)$ is the degree of vertex i (i.e., the number of edges connected to vertex i), and N is the total number of vertices in the network.

C. Network Cohesion

Network cohesion measures were used to assess how interconnected the co-authorship network is:

- Network** **Density:**
 Density represents the ratio of observed to possible edges:

$$den(G) = \frac{|E_G|}{|V_G|(|V_G| - 1)/2}$$

Where $|E_G|$ is the number of edges in graph G and $|V_G|$ the number of vertices in graph G .

- Clustering Coefficient** **Transitivity:**
 This indicates the extent to which nodes tend to cluster together. It is calculated as the ratio of the number of closed triplets (triangles) to the total number of connected triplets:

$$cl_T(G) = \frac{3\tau_\Delta(G)}{\tau_3(G)},$$

where $\tau_\Delta(G)$ is the number of triangles in the graph G , and $\tau_3(G)$, the number of connected triples.

- Giant** **Component:**
 The largest connected subgraph in which each node is reachable from any other. Its presence indicates strong overall network connectivity.
- Average Path Length and Diameter:**
 These metrics reflect the efficiency of information flow. The diameter is the longest shortest path between any two nodes, while the average path length is the mean of all shortest paths.

D. Assortativity

Assortativity measures the tendency of nodes with similar attributes (e.g., region, institution type) to connect. The assortativity coefficient, which is similar to a correlation coefficient, quantifies this tendency:

$$r_a = \frac{\sum_i f_{ii} - \sum_i f_{i+} f_{+i}}{1 - \sum_i f_{i+} f_{+i}},$$

where f_{ij} is the fraction of edges in G that join a vertex in the i th category with a vertex in the j th category, f_{i+} and f_{+i} denote the i th marginal row and column sums, respectively, of the resulting matrix f .

Analysis

Table 1

Journals and Distribution of papers published with the number of authors

Jornal	Year	Number of papers	Authors
RSS	2024	25	75
NSA	2020	4	40
	2021	5	
	2022	6	
	2023	5	
CBN	2020	11	35
	2021	5	

Table 1 shows that between 2020 and 2024, a total of 61 papers were published across three major Nigerian statistical journals (CBN, RSS, and NSA), demonstrating a robust yet varied pattern of collaboration. The CBN journal produced 16 papers with 35 authors, RSS contributed 25 papers with 75 authors, and NSA added 18 papers with 40 authors, reflecting average authorship ranging from just over 2 to 3 per paper.

Table 2

Number of Institutions Published in each Journal

Journal	Number of Institutions
CBN	12
RSS	36
NSA	20

Table 2 shows that authorship across the three journals spans a diverse institutional landscape, with varying levels of representation. RSS exhibits the widest institutional reach, followed by NSA, while CBN has the most concentrated pool of contributors.

Figure 1

Top 7 Institutions with the highest number of authors

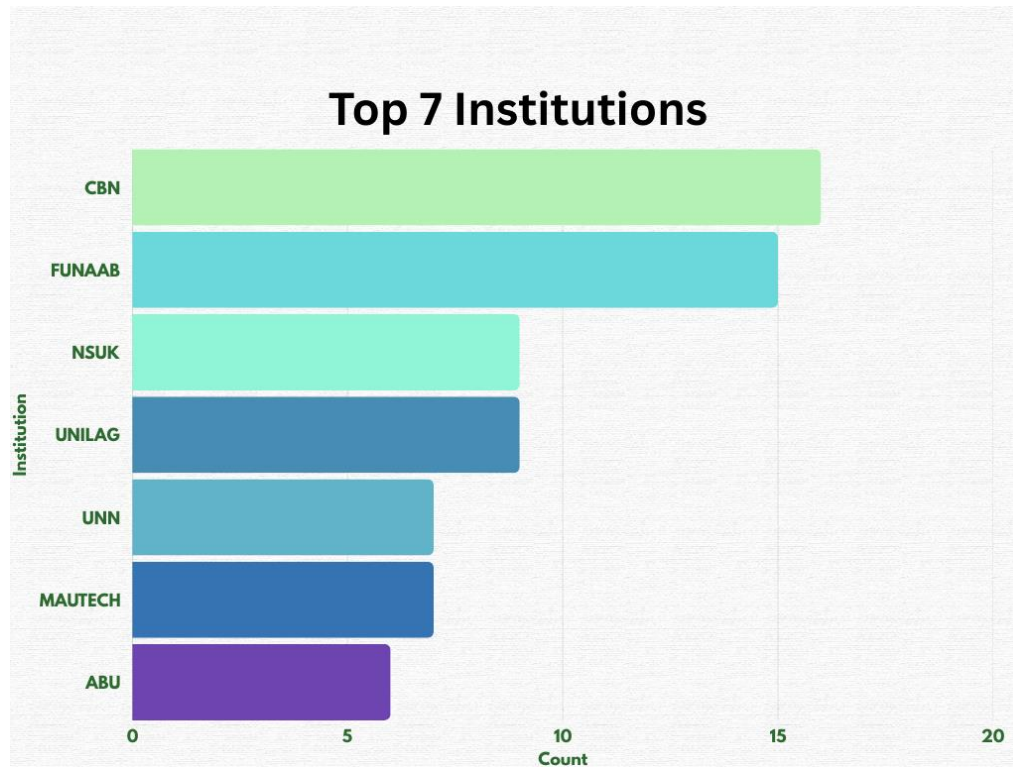


Figure 1 above shows that the Central Bank of Nigeria(CBN) and the Federal University of Agriculture Abeakuta(FUNAAB) has the highest number of authors who have published in these journals from 2020 to 2024. Out of the 57 Institutions the authors are from.

Figure 2

Distribution of co-authors per paper

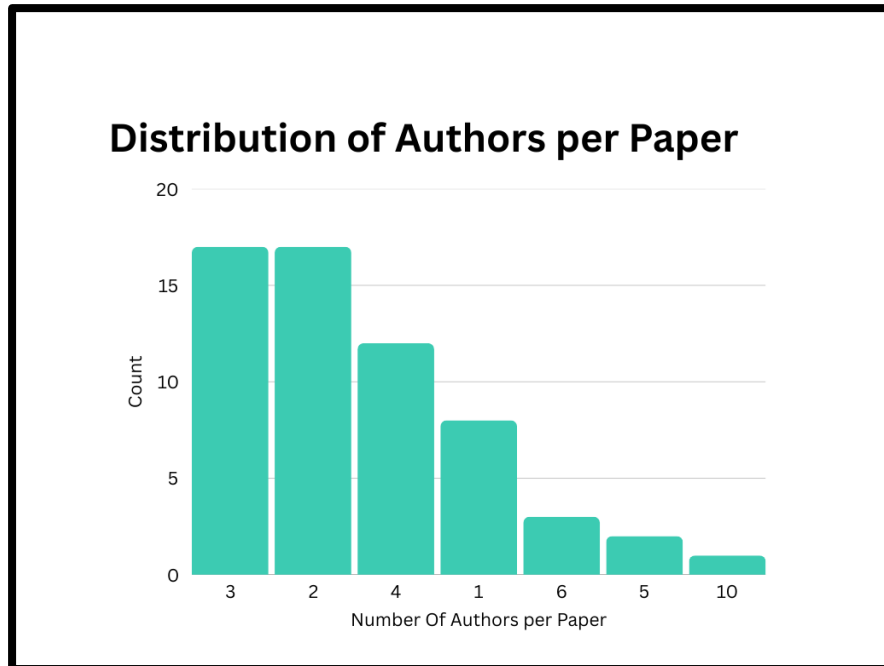
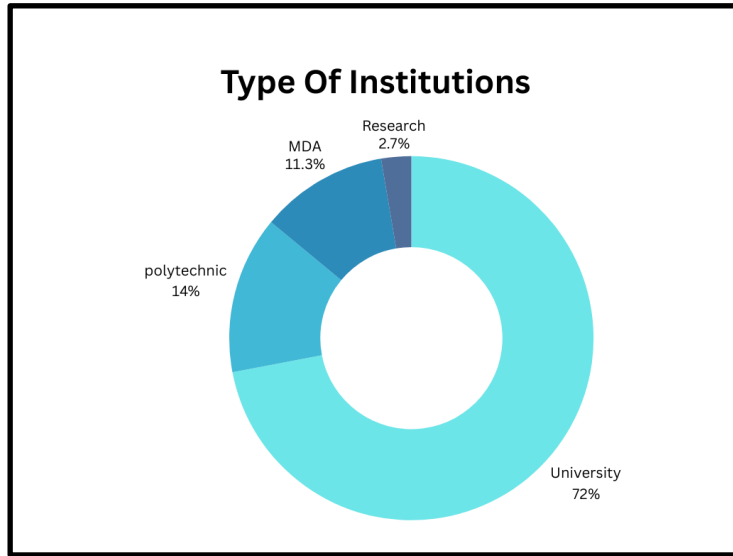


Figure 2 shows that there are 34 papers with 3 or 2 authors of the 61 papers published in the 3 journals. That is 51.52% have 3 or 2 authors, 12% of the papers have one author and the rest have 4, 6, 5 and 10 authors.

Figure 3

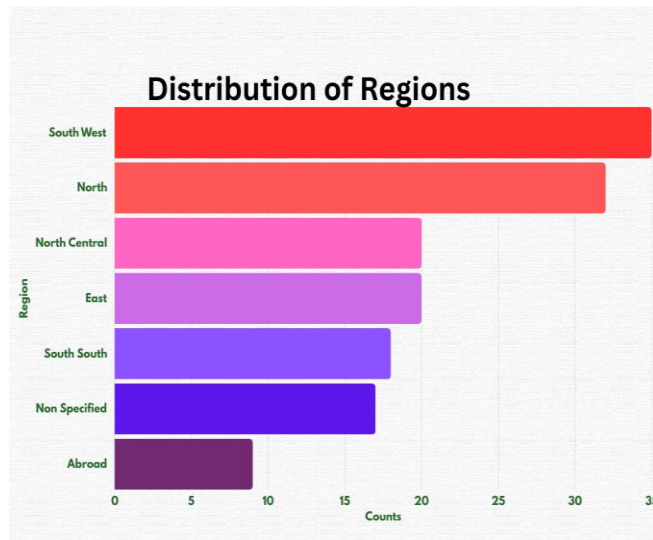
Pie chart for the Type of Institutions the Authors belong to.



There are four types of Institutions (figure 3). Most authors are from the university (72%). The remaining 38% of authors are not evenly distributed among the remaining Type of Institutions. Authors from Research Institutions are not many (2.7%)

Figure 4

Frequency of Regions



Authors from all the regions of the country have published in the journals (figure 4). The south west has more authors (35). Following closely are the North (32) and North Central regions. Some authors' location was not specified (17), and 9 authors are from abroad.

Figures 5

Co-author Network

Figures 6

Co-author Network and their Type Of Institution

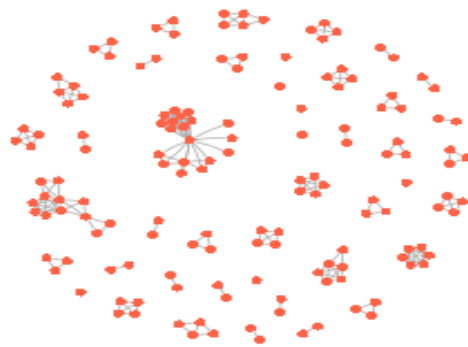
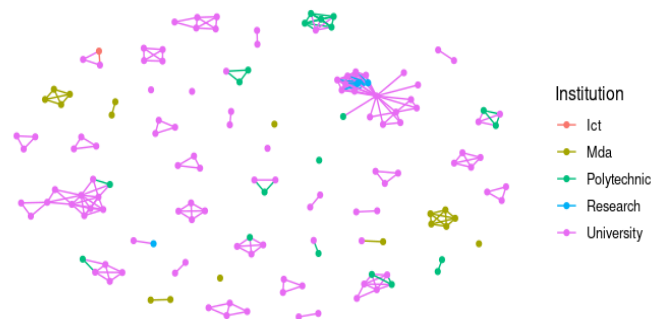


Table 3

Co-author network Key Statistics

Network statistics	Value
Nodes	149



Edge	226
Density	0.02
Average Degree	3.0
Clustering	0.807
Average Path length	1.439
Diameter	3
Giant Component	19

The network is sparse, undirected, and not connected (figures 5&6). The network has the small world properties on social networks (Average Path length - 1.439 and clustering 0.8). The attributes of the network include the Institution the author belong to, the Type of Institution the belong to and the region their institution is located with the country.

Table 4

Centrality Measures of the 5 Top-Ranked Authors

Name	Institute	Number Of Papers	Betweenness	Degree	Closeness	Rank
Monday Osagie Adenomon	Nasarawa State University Keffi	8	106	18	0.06	1
Wale-Orojo Oluwaseun Ayobami	Federal University of Agriculture, Abeokuta	3	20	9	0.08	2
Eno Emmanuella Akarawak	University of Lagos	2	1.5	5	0.2	3
Ismail Adedeji Adeleke	University of Lagos	2	1.5	5	0.2	4

Atanda Omolola Dorcas	St. Andrews College, Cambridge	2	8	7	0.07	5
--------------------------	--------------------------------------	---	---	---	------	---

Monday Osagie Adenomom is the most influential author in the network. He is the only author who has published in two of the three journals and has co-authored more than five published journals in the network (table 3). The centrality measures show us that authors from four Institutions are central to the co-author network.

Figure 7

Second Largest Co-author component

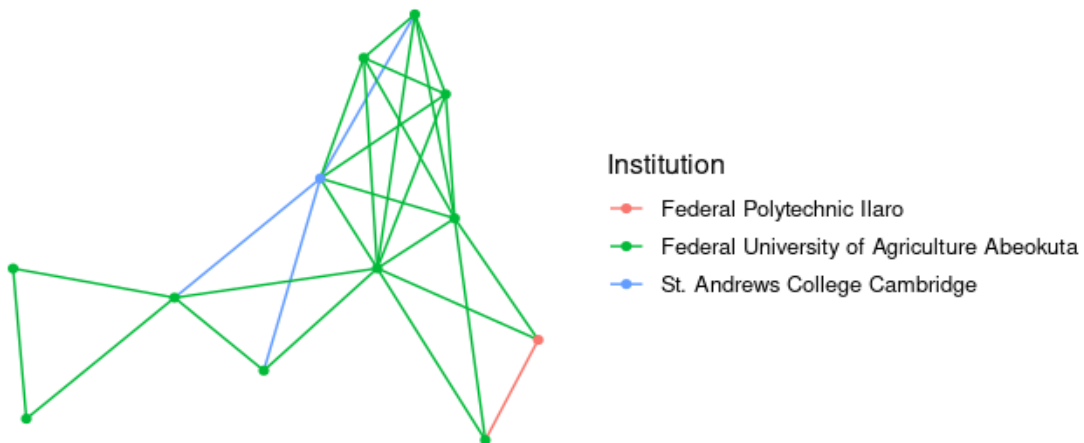


Figure 8

Largest Co-author Network Component

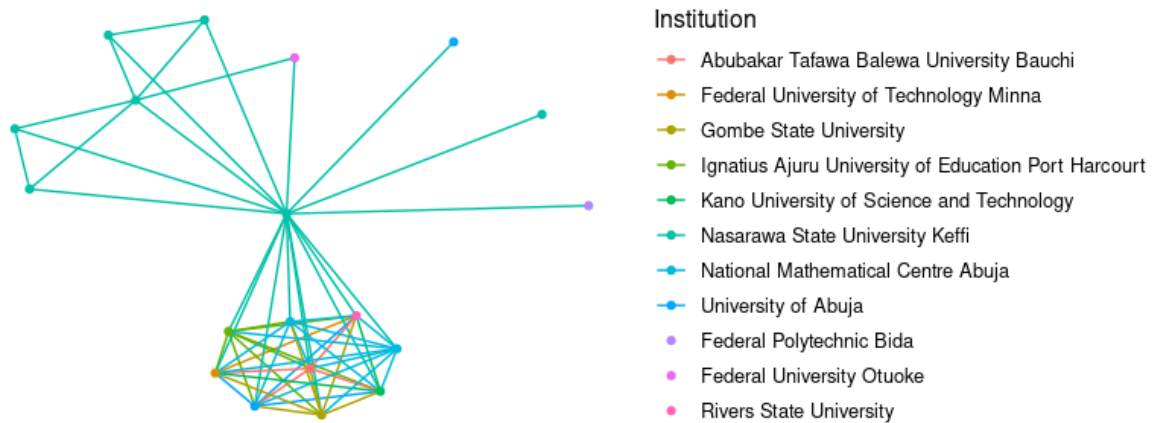


Table 5

The two largest components network statistics

Network Statistic	Component 1	Component 2
Nodes	19	12
Edges	61	28
Average path length	1.64	1.76
clustering	0.77	0.67

Figures 7&8 are the two distinct and largest components in the network. They have 12 nodes and 28 edges, and 19 nodes and 61 edges, respectively. Component 1 has authors from 11 institutions that form it, while Component 2 has 3 institutions.

Table 6

Assortativity values of attribute values

Attribute Type	Value	Assortativity value
Institution	CBN	0.971
Region	South West	0.761
Institute Type	University	0.43

Table 6 shows the Assortativity of the Top Attribute type. The network exhibits strong institutional homogeneity, with CBN authors showing the highest tendency to collaborate within their institution. Regional connections, particularly in the South West, also reflect a notable degree of Assortativity, though with slightly more openness. Collaboration based on institute type, while still present, is the weakest of the three, indicating a relatively more mixed pattern of interactions across universities and other Types of institutions (Table 5)

Discussion

This study constructed a co-authorship network from three statistical journals: *The Central Bank of Nigeria Journal of Applied Statistics*, *The Journal of the Nigerian Statistical Association*, and *The Journal of the Royal Statistical Society Nigeria Group*. A total of 61 papers published between 2020 and 2024 were analysed. The distribution of papers and the number of authors across the journals show consistent co-authorship trends, though the degree of collaboration varies. Notably, *The Journal of the Royal Statistical Society Nigeria Group* exhibited a slightly higher tendency toward multi-authored publications. Using the `igraph` package in R, we found that the co-authorship network consisted of 149 authors connected through 226 co-authorships. The network had a low density of 2%, suggesting limited overall collaboration—most authors do not frequently co-author papers with others. Despite this, the network displayed a relatively high clustering coefficient of 0.807, indicating that when collaboration does occur, it tends to happen in closed groups or research clusters. Further analysis revealed the network comprises multiple components, with the two largest containing 12 authors (18%) with 28 connections and 19 authors (28%) with 61 connections, respectively. The most influential author was found in the larger component of 19 authors.

The network also exhibited a small-world property, a common characteristic of social networks. This is supported by an average path length of 1.4 and a high clustering coefficient, reinforcing the presence of tight-knit communities within the network.

To identify key contributors, we examined centrality measures including degree, closeness, and betweenness centrality. Five authors emerged as central to collaboration within the network: Monday (8 papers), Wale-Orojo (3), Eno (2), Ismail (2), and Atanda (2). Monday ranked highest in all three centrality measures. With a degree centrality of 18, Monday had the most co-author connections. A betweenness centrality score of 106 also indicated that Monday serves as a crucial bridge connecting different authors. Furthermore, Monday had the highest closeness centrality, implying proximity to most other authors in the network. Interestingly, Monday was the only author to publish in two of the three journals, co-authoring eight papers.

To understand the role of proximity in collaboration, we measured assortativity based on institutional and regional attributes. Assortativity coefficients, which range from -1 to 1, indicate the extent to which authors tend to collaborate with others who share similar attributes.

- The assortativity score based on institutional affiliation was 0.9, indicating a strong tendency for authors to collaborate with others from the same institution.
- The assortativity score by region was 0.7, suggesting a high level of regional collaboration, with authors more likely to co-author with others from the same geographical area.
- The assortativity score based on institution type (e.g., universities, government agencies, research institutes) was 0.4, indicating a moderate tendency for authors to collaborate within the same type of institution, though there was also some level of cross-type collaboration.

These findings suggest that institutional and geographic proximity play a significant role in collaboration, which may explain the network's low density but high clustering.

The strength of collaboration (edge weight) was not included in this analysis, and the graph was simplified. As a result, some authors may have additional co-authorships outside the scope of these three journals. While comprehensive co-authorship studies focused on Nigerian journals are still limited, existing research supports our findings. For example:

- (Moayednia et al., 2014) notes low network cohesion in JRMS, with a density of 0.0806 (8.06%).
- In the Malaysian Journal of Mathematical Sciences (2019), the density was just 0.009 (0.9%).
- (Baggio et al., 2008) highlights the impact of geographic barriers and the need for improved collaboration.

These studies reinforce the idea that low-density, tightly clustered networks are common in academic collaboration, often shaped by institutional and regional boundaries. In some graduate networks, the rise of core research groups suggests a shift toward greater collaboration, even if overall density remains low (Chuan-Yi et al., 2016, Baggio et al., 2008 & Santonen & Ritala, 2014).

Conclusion

Taken together, our findings suggest that a significant number of authors are not publishing across the available statistical journals, and that collaboration remains limited outside familiar institutional or regional circles. Authors tend to work with colleagues nearby, either physically or institutionally, rather than building wider research connections. Future studies should investigate the reasons behind the lack of cross-institutional collaboration, possibly through surveys or interviews. Expanding this type of analysis to include more journals and international publications could provide a fuller picture of collaboration patterns within and beyond the Nigerian statistical research community. This study contributes by mapping the structural features of academic collaboration in Nigerian statistics, highlighting the roles of key contributors, and offering insights into institutional clustering and collaboration patterns.

Recommendation

Based on the results and interpretations of the research, it is suggested that:

1. Encourage Inter-Institutional Research Grants and Projects: Given the dominance of intra-institutional collaborations, funding agencies and research bodies should incentivise cross-institutional teams through targeted research grants to bridge institutional silos.
2. Journal Policies to Foster Collaboration: Editorial boards could encourage multi-authored and multi-institutional submissions by prioritizing such papers in special issues or giving visibility to collaborative works in their promotion efforts.
3. Mentorship and Inclusion of Early-Career Researchers: Since the network is centered around a few influential researchers, institutions and journals should promote mentorship programs to integrate early-career statisticians into ongoing research, expanding the collaborative base.
4. Use of Research Collaboration Platforms: Institutions should adopt or develop digital platforms (e.g., Slack groups, research repositories) to connect statisticians working on similar themes, fostering thematic research clusters beyond geographical boundaries.

References

- Abbas, K. D. (2016). Patterns of Scholarly Collaboration among Academics in Nigerian Universities: Knowledge Sharing or Knowledge Hoarding? *DergiPark (Istanbul University)*. <https://dergipark.org.tr/tr/pub/jblu/issue/27674/291684>
- Afolabi, I. T., Ayo, A., & Odetunmbi, O. A. (2021). Academic Collaboration Recommendation for Computer Science Researchers Using Social Network Analysis. *Wireless Personal Communications*, 121(1), 487–501. <https://doi.org/10.1007/s11277-021-08646-2>

- Almuhanna, A. A., Yafooz, W. M. S., & Alsaeedi, A. (2022). An interactive scholarly collaborative network based on academic relationships and research collaborations. *Applied Sciences*, *12*(2), 915. <https://doi.org/10.3390/app12020915>
- Baggio, R., Scott, N., & Arcodia, C. (2008). *Collaboration in the events literature: a co-authorship network study*.
- Biscaro, C., & Giupponi, C. (2014). Co-Authorship and bibliographic coupling network effects on citations. *PLoS ONE*, *9*(6), e99502. <https://doi.org/10.1371/journal.pone.0099502>
- Carchiolo, V., Grassia, M., Malgeri, M., & Mangioni, G. (2022). Co-Authorship Networks Analysis to Discover Collaboration Patterns among Italian Researchers. *Future Internet*, *14*(6), 187. <https://doi.org/10.3390/fi14060187>
- Chuan-Yi, W., Xiao-Hong, L., & Yi, C. (2016). An empirical study on the collaboration of scholars in graduate education. *ICIIP*, *9*, 1–7. <https://doi.org/10.1145/3028842.3028878>
- Fagan, J., Eddens, K. S., Dolly, J., Vanderford, N. L., Weiss, H., & Levens, J. S. (2018). Assessing Research Collaboration through Co-authorship Network Analysis. *PubMed*, *49*(1), 76–99. <https://pubmed.ncbi.nlm.nih.gov/31435193>
- Fari, S. A., & Ingawa, A. I. (2020). Analysis of Factors Influencing Academic Collaborative Research in Selected Federal Universities in Nigeria. *MBJLIS – Middlebelt Journal of Library and Information Science*, Vol. 18, 2020, 18. <https://www.mbjlisonline.org/index.php/jlis/article/view/4>
- Lewis, J., Ross, S., & Holden, T. (2012). The how and why of academic collaboration: Disciplinary differences and policy implications. *Higher Education*, *64*(5), 693–708.
- Moayednia, R., Shokri, D., Mobasherizadeh, S., Baradaran, A., Fatemi, S. M., & Merrikhi, A. (2014). Study of the co-authorship network of papers in the Journal of Research in Medical Sciences using social network analysis. *PubMed*. <https://pubmed.ncbi.nlm.nih.gov/25002893>
- Morel, C. M., Serruya, S. J., Penna, G. O., & Guimarães, R. (2009). Co-authorship Network Analysis: a powerful tool for strategic planning of research, development and capacity building programs on neglected diseases. *PLoS Neglected Tropical Diseases*, *3*(8), e501. <https://doi.org/10.1371/journal.pntd.0000501>
- Mydin, F., Rahman, R. S. a. R. A., & Mohammad, W. M. R. W. (2021). Research Collaboration: Enhancing the research skills and Self-Confidence of early career academics. *Asian Journal of University Education*, *17*(3), 142. <https://doi.org/10.24191/ajue.v17i3.14508>
- Network effects are critical for research collaborations.* (n.d.). CEPR. <https://cepr.org/voxeu/columns/network-effects-are-critical-research-collaborations>
- Newman, M. E. J. (2004). Coauthorship networks and patterns of scientific collaboration. *Proceedings of the National Academy of Sciences*, *101*(suppl_1), 5200–5205. <https://doi.org/10.1073/pnas.0307545100>
- Oyeniya, Oluwakemi, J., Olaifa, & Paul, T. (2012). Collaborative strength and pattern of authorship among agricultural engineers in Nigeria: A case study of the 2000 - 2010 NIAE proceedings. *INTERNATIONAL JOURNAL OF LIBRARY AND INFORMATION SCIENCE*, *4*(6), 115–120. <https://doi.org/10.5897/ijlis.9000023>
- Roslan, H., Nurain, I. Y., Fateme, S. M., Rudrusamy, G. & Sumarni, A. B. (2019). The Co-Authorship Network Analysis Of Research Papers In The Malaysian Journal Of Mathematical Sciences In 2019. (N.D.). *Journal of Mathematical Sciences and Informatics*. <https://doi.org/10.46754/jmsi.2023.06.003>
- Sameer Kumar, S. (2015). Co-authorship Networks: A review of the literature. *Aslib Journal of Information Management*, *67*(1), 55–73. <https://doi.org/10.1108/AJIM-09-2014-0116>
- Santonen, T., & Ritala, P. (2014). SOCIAL NETWORK ANALYSIS OF THE ISPIM INNOVATION MANAGEMENT COMMUNITY IN 2009–2011. *International Journal of Innovation Management*, *18*(01), 1450010. <https://doi.org/10.1142/s1363919614500108>
- Ullah, M., Shahid, A., Din, I. U., Roman, M., Assam, M., Fayaz, M., Ghadi, Y., & Aljuaid, H. (2022). Analyzing interdisciplinary research using Co-Authorship networks. *Complexity*, *2022*(1). <https://doi.org/10.1155/2022/2524491>