Computer Engineering and Applications Vol. 14, No. 1, February 2025

Analyzing Co-Authorship Networks in Indonesian PTN-BH Institution Through Social Network Analysis

Firdaus[1], Siti Nurmaini[1*], Anggy Tias Kurniawan[1], Annisa Darmawahyuni[1], Muhammad Naufal Rachmatullah[1], Sarifah Putri Raflesia [2], Dinda Lestarini[2]
[1]Intelligent System Research Group, Universitas Sriwijaya, Palembang 30137, Indonesia
[2]Faculty of Computer Science, Universitas Sriwijaya, Palembang 30137, Indonesia
Coresponding Author's E-Mail: siti_nurmaini@unsri.ac.id

ABSTRACT

This study involved an examination of bibliographic information from Indonesia. Our approach centered on utilizing social network analysis to explore the co-authorship relationships among Indonesian authors, focused on the co-authorship network within the context of authors affiliated with Indonesian state universities known as "PTN-BH," which specialize in higher education and legal studies. To conduct our analysis, we gathered publication data from the Scopus database, spanning a time frame from 1948 to 2020. The primary methodology entailed constructing a graph composed of nodes and edges, representing the co-authorship connections among these authors. By employing the Louvain method, we were able to identify prominent communities within this graph. We carried out a comprehensive analysis at both macro and micro levels, involving measurement techniques tailored to these perspectives. Through this approach, we revealed and examined the collaboration patterns among authors associated with PTN-BH institutions, as illuminated by the co-authorship network analysis.

Keywords: bibliographic; Indonesia; Scopus; co-authorship network analysis

1. INTRODUCTION (10 PT)

In 2018 and 2019 there has been a very significant growth of Indonesian publications (Bayu et al., 2020). The rise in publication activity has led to an increase in the number of authors and a broader range of academic fields in Indonesia. It is essential to assess and evaluate the level of collaboration among authors within the country(Farhan Bashir et al., n.d.; Munoz et al., 2016).

Social network analysis (SNA) has become a valuable approach for evaluating interdisciplinary science through the examination of different collaboration networks(Li & Huang, 2023; Si, 2022; Stieglitz et al., 2014). Co-authorship networks have been extensively employed to understand how scientific collaboration is organized and to gauge the reputation of individual researchers(Fagan et al., 2018; Liu et al., 2005). This method has been utilized across diverse domains, including mathematics, neuroscience, and various information systems, to uncover insights from the patterns of co-authorship and collaboration (Soria Mateo et al., 2013).

A co-authorship network represents the connections between authors who have collaborated on scientific publications(Thanoon et al., 2021). It highlights the co-authorship relationships that indicate whether authors have jointly contributed to research papers. These relationships reveal whether authors have collaborated with one another on writing academic articles (Umadevi, 2013). The use of co-authorship networks to measure research collaboration has started since the 1960s (Kumar, 2015). Engaging in research collaboration plays a pivotal role in effectively channeling talents, ideas, and knowledge to the public(Abramo et al., 2011). By and large, research collaboration serves as a bridge that connects different fields of study, enabling them to jointly address specific challenges and derive research outcomes from these issues(Hwang et al., 2020; Lang et al., 2012; Sun et al., 2020). In straightforward language, research collaboration brings different ideas together to create fresh and innovative research.

The number of research publications is rapidly growing across all academic disciplines, and this surge has sparked significant interest in analyzing co-authorship networks. However, dealing challenging and complex due to the exponential expansion of scientific publications (Aggrawal & Arora, n.d.; Kwilinski, 2023).

The overall structure of the network can be understood from both a broad perspective and a detailed viewpoint. On the larger scale, macro-level analysis involves assessing graph density, clustering coefficients, and degree distribution. On the other hand, at the micro level, the focus shifts to individual nodes, where centrality measurements such as betweenness centrality, closeness centrality, and eigenvector centrality are computed.

This study adopts a social network concept akin to the co-authorship network but focuses on the network of authors in the context of research papers. In this network, authors are depicted as nodes, and their connections are illustrated as edges(Camacho et al., 2020; Savić et al., 2015). The research draws upon a substantial dataset, specifically publication data sourced from Indonesian state universities (PTN-BH) that specialize in higher education and legal studies and are recognized as prominent educational institutions within Indonesia.

2. METHOD

A. Data Collection

In this study, we extracted publication data from authors affiliated with PTN-BH institutions, which was collected from Scopus on November 15, 2019. Out of the 14 available variables, we specifically focused on the author(s) ID variable to serve as the source for nodes in the network, corresponding to each publication. This effort resulted in successfully obtaining 67,133 publications, spanning from the year 1948 to 2020. Among the PTN-BH universities, Universitas Indonesia (UI) recorded the highest publication count at 14,831, while Universitas Pendidikan Indonesia (UPI) had the lowest with 2,289 publications Figure 1.

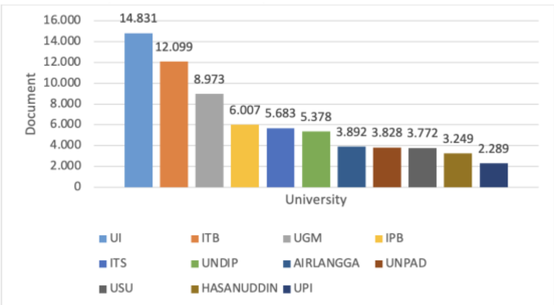

Fig. 1. Number of PTNH-BH Universities Publications by 2010-2020.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

The data reveals that Universitas Indonesia (UI) exhibits the most significant upward trend in publication numbers, as depicted in Figure 2.

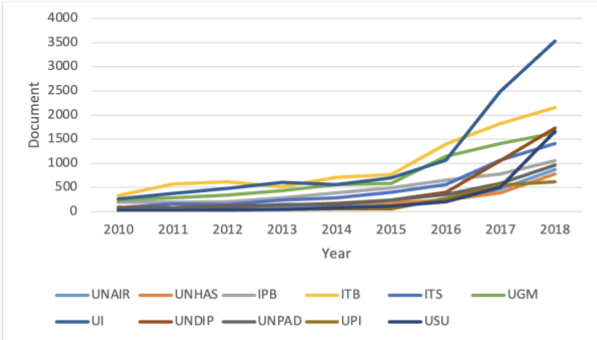

Fig. 2. Trends of PTNH-BH Universities Publications by 2010-2018.

Furthermore, it's noteworthy that overall, all PTN-BH universities show a growth pattern in their publication counts. Figure 3 demonstrates that Universitas Indonesia (UI) holds the largest count of authors (nodes) among the 11 PTN BH Universities. Following UI, the Bandung Institute of Technology (ITB) ranks second, and Universitas Gadjah Mada (UGM) secures the third position. In Figure 4, the highest number of co-authorships (edges) is attributed to UI, while Hasanuddin University and Universitas Diponegoro (UNDIP) rank second and third, respectively. Among all the PTN BH universities, Universitas Pendidikan Indonesia (UPI) has the lowest count of authors (nodes) and co-authorships (edges).

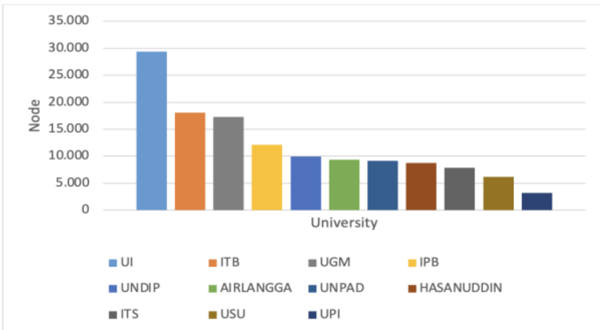

Fig. 3. Number of PTNH-BH Universities Author (Node) by 1948-2020.

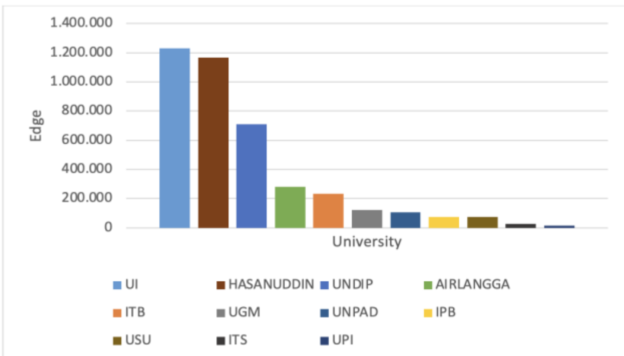

Fig. 4. Number of PTNH-BH Universities Co-authorship (edge) by 1948-2020.

B. Data Visualization and Processing

To enhance the visual representation and facilitate a clearer understanding of the graph, the application of a layout algorithm is essential. In this experiment, the OpenOrd Layout is employed, working in conjunction with the Gephi Software. Gephi serves as a tool for visualizing and exploring various types of graphs, with the primary objective of assisting data analysts in generating hypotheses and uncovering intuitive patterns.

The subsequent step involves conducting comprehensive calculations and analyses on both a broader scale and a more detailed perspective. The goal is to explore and identify communities that have emerged within the network structure. This analytical phase provides valuable insights, such as determining authors with the highest number of connections to their peers, identifying authors with minimal or no connections, and assessing the size of the communities established within the co-authorship network.

The concept of modularity is harnessed to detect and delineate distinct communities within the network(Newman, 2006). Modularity assists in identifying clusters of authors who share strong collaboration ties and common research interests. Moreover, the average degree metric is employed to assess the distribution of connections for each individual node within the network(Phillips et al., 2019). This facilitates a clearer understanding of how extensively authors are connected and the patterns of collaboration that exist among them. The Clustering Coefficient is utilized to gauge the strength of connections between nodes and their neighboring nodes within the network(Kong et al., 2019). Graph Density, on the other hand, serves as a measure of how closely interconnected the entire network is(González-Alcaide et al., 2020). Eigenvector centrality offers a relative influence score for authors, reflecting their prominence within the network. Network Diameter is a metric used to ascertain the betweenness value of an author, highlighting their significance as a bridge connecting different parts of the network.

Prior to embarking on the calculations for macro and micro level measurements, an exploration of communities within the co-authorship network was undertaken. The Louvain method was employed as the technique to identify and delineate these communities. This process involved detecting and categorizing groups of authors who collaboratively contribute to specific research areas or themes within the network. The Louvain method presents an algorithm that efficiently identifies well-structured divisions within a large network. This method is particularly adept at swiftly revealing modular partitions, allowing for the exploration of hierarchical community structures within the network.

C. Macro-Level Measurement

At the macro level, computations were conducted using Gephi, which offers the necessary tools for performing various analyses on the established network. Three specific measurements were employed for macro-level assessment, each facilitated by Gephi (Silva et al., n.d.):

- Degree Distribution Measurement: This assesses the distribution of connections among nodes within the network, shedding light on the connectivity patterns of authors.
- Graph Density Measurement: This metric gauges how closely interlinked the network is as a whole, providing insights into the overall cohesion of the co-authorship relationships.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

- Clustering Coefficient Measurement: This measurement evaluates the degree to which nodes and their neighboring nodes are interconnected, indicating the presence of local clusters or communities within the network.

For quantifying the degree distribution of each node in the network, we employed data input encompassing an Adjacency Matrix (M) Graph, alongside the total count of nodes (nn) present within the network. It generated an output, depicted in figure 5, showcasing the degree distribution (dc) for each individual node in the graph. This measurement helps illustrate how well-connected each author is within the collaborative network.

```
Pseudocode Degree Distribution
  Data: Adjacent matrix M of the graph and number of nodes nn
  Result: Degree Distribution dc of vertices in the graph

Initiate dc array with nn positions containing 0;
for i ← 0 to nn do
|  for j ← 0 to nn do
|  |  if i ≠ j then
|  |  |  dc[i] ← dc[i] + M[i ][ j ];
|  |  end
|  end
end
return dc;
```

Fig. 5. Degree distribution pseudocode

To quantify the graph density within a network, we employed input data that encompassed both the total count of nodes (nn) and the total count of edges (ne) present within the network. By utilizing this input, we generated an output value representing the graph density (gd) of the network, as depicted in Figure 6. This measurement offers insight into the level of interconnectivity and cohesion within the collaborative network.

```
Pseudocode Degree Distribution
  Data: Number of nodes nn and number of edges ne
  Result: Graph Density gd of network in the graph

Initiate nn and ne;
gd ← 2 * ne / nn * (nn − 1)
return gd;
```

Fig. 6. Graph density pseudocode.

To determine the clustering coefficient for each node within the graph, the calculation involves using an Adjacency Matrix (M) Graph along with the total count of nodes (nn) present in the network as input data. The result of this computation is the clustering coefficient (cc) for each individual node in the graph, as depicted in Figure 7. This coefficient provides insights into the level of local clustering or community formation around each node within the network.

```
Pseudocode Clustering Coefficient
  Data: Adjacent matrix M of the unweighted graph and number of nodes nn
  Result: Clustering coefficient cc of vertices in the unweighted graph

Calculate the degree centrality k of vertices;
Powering the matrix M to the power of 3;
Initiate cc array with nn positions containing inf;
for i ← 0 to nn do
 |  denominator ← k[i] * (k[i] − 1);
 |  if denominator ≠ 0 then
 |   |  cc[i] ← M[i ][i ]/denominator;
 |  end
end
return cc;
```

Fig. 7. Pseudocode Clustering Coefficient

D. Micro-Level Measurement

At the macro level, Gephi was harnessed to facilitate comprehensive calculations within the formed network. As illustrated in Figure 8, the pseudocode outlines the procedure used to compute the betweenness centrality value for each node in the graph. This operation leverages input data, specifically an Adjacency Matrix (M) Graph and the total node count (nn) within the network. The outcome of this computation is the betweenness centrality (bc) value attributed to each node in the graph.

```
Pseudocode Betweenness Centrality
  Data: Adjacent matrix M of the graph and number of nodes nn
  Result: Betweenness Centrality bc of vertices in the graph

Initiate bc array with nn positions containing 0;
for i ← 0 to nn do
 |  for j ← 0 to nn do
 |   |  if i ≠ j then
 |   |   |  Count the number of shortest paths nsp between vertices i and
 |   |   |   j ;
 |   |   |  for k ← 0 to nn do
 |   |   |   |  if k ≠ i and k ≠ j then
 |   |   |   |   |  Count the number of shortest paths nspk between
 |   |   |   |   |  vertices i and j that pass through vertex k;
 |   |   |   |   |  if nsp ≠ 0 then
 |   |   |   |   |   |  bc[k] ← bc[k] + nspk/nsp;
 |   |   |   |   |  end
 |   |   |   |  end
 |   |   |  end
 |   |  end
 |  end
end
return bc;
```

Fig. 8. Betweenness centrality pseudocode

Similarly, Figure 9 depicts the process of calculating the closeness centrality value for each node in the graph. This computation relies on input data involving an Adjacency Matrix (M)

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

Graph and the total node count (nn) within the network. The result of this calculation is the closeness centrality (cc) value assigned to each node.

```
Pseudocode Closeness Centrality
  Data: Adjacent matrix M of the graph and number of nodes nn
  Result: Closeness Centrality cc of vertices in the graph

Calculate the distance d for every pair of nodes;
Initiate cc array with nn positions;
for i ← 0 to nn do
 |  cc[i] ← 0;
 |  for j ← 0 to nn do
 |   |   if i ≠ j then
 |   |   |   if d[i ][j ] ≠ inf then
 |   |   |   |  cc[i] ← cc[i] + d[i ][j ];
 |   |   |   end
 |   |   end
 |  end
 |  if cc[i ] ≠ 0 then
 |   |  cc[i] ← 1.0/cc[i ];
 |  end
end
return cc;
```

Fig. 9. Closeness Centrality pseudocode.

Furthermore, in Figure 10, the computation of the eigenvector centrality value for each node in the graph is outlined. This operation employs input data, namely an Adjacency Matrix (M) Graph and the total node count (nn) within the network. The outcome is the eigenvector centrality (ec) value assigned to each node. These centrality metrics offer insights into the prominence and influence of individual nodes within the network.

```
Pseudocode Eigenvector Centrality
  Data: Adjacent matrix M of the graph and number of nodes nn
  Result: Eigenvector Centrality ec of vertices in the graph

Initiate ec array with nn positions containing their index (starting with 1);
lambd ← inf;
lambdnew ←−inf;
while abs(lambd − lambdnew) > 0.000001 do
  |  lambd ←lambdnew;
  |  ecnew ←multiplication of M with ec;
  |  lambdnew ← norm(ecnew)/norm(ec);
  |  ec ← normali ze(ecnew);
end
return ec;
```

Fig. 10. Pseudocode Eigenvector Centrality.

3. RESULTS AND DISCUSSION

The resultant network comprises a total of 111,984 nodes and 3,002,044 edges. Within this network, nodes symbolize authors, while edges signify co-authorship connections between these authors. Notably, the structure of the network is undirected and unweighted, as illustrated in Table 1.

Table 1 - Co-Authorship Network Information

Node	Author
Edge	Co-authorship
Network Format	Undirected
Edge weights	Un-weighted
Size	111.984 nodes (authors)
Volume	3.02.44 ges (co-authorship)

A. Community Detection

The outcomes of community detection are depicted in Figure 11, showcasing the communities that have emerged. In total, there are 2,479 distinct communities identified. The most substantial community consists of 291 members, representing 17.7% of the entire network. Notably, communities with a contribution of less than 4.55% are depicted in gray color within the displayed graph.

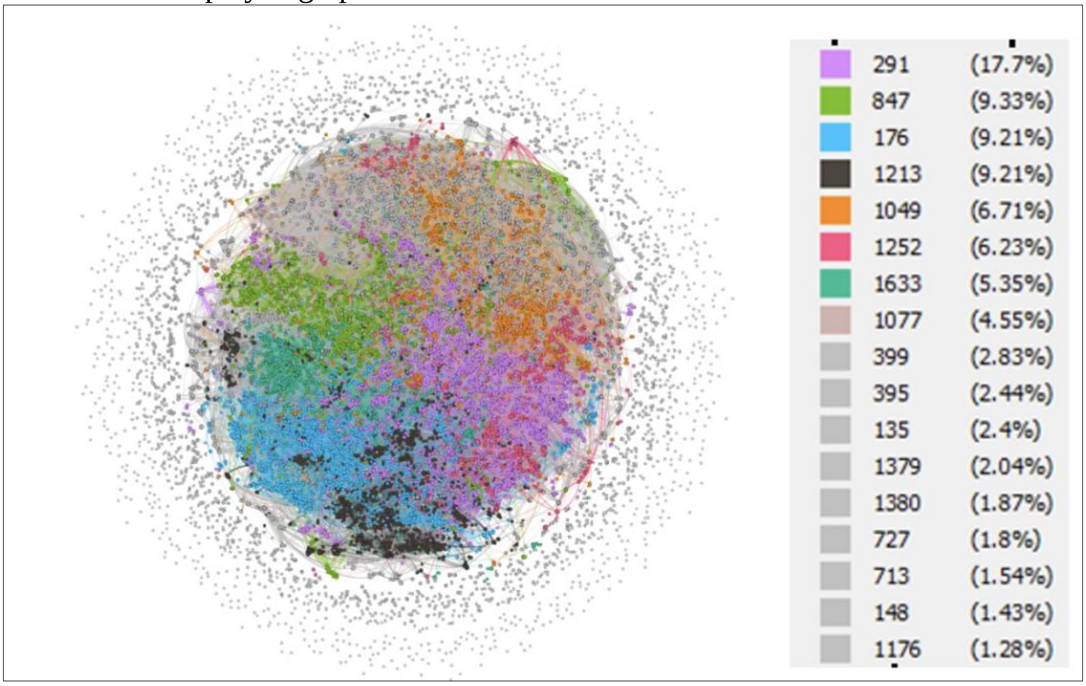

Fig. 11. Visualization of Graph with Community

For a more detailed view, the visualization of the three largest communities within the co-authorship network can be observed in Figure 12, and their attributes are summarized in Table 2.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

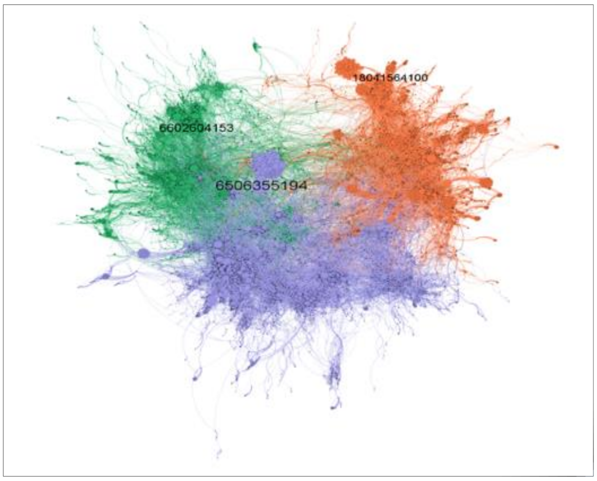

Fig. 12. The Three Largest Communities Of Co-Authorship Network.

Table 2. Top Three Authors with Highest Degree

Author id	Degree Distribution	Clustering Coefficient
18041564100	339	0.092632
6506355194	337	0.203988
6602604153	284	0.017469

B. Giant Component

The term "giant component" refers to a network subset comprising nodes that are connected at maximum in the entire network. The giant components of the overall network are illustrated in Figure 13.

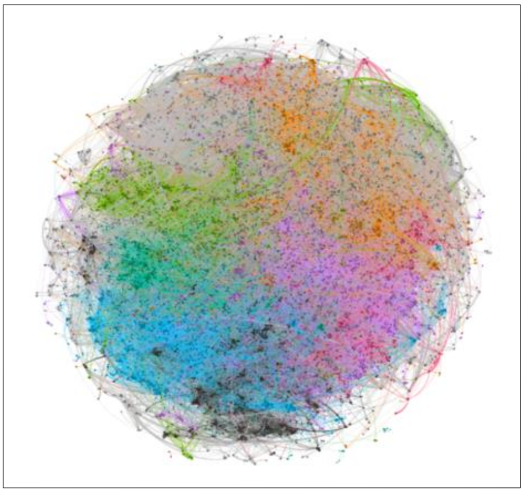

Fig. 13. Giant Component Visualization.

When comparing the giant component to the entire network, there are disparities in the count of nodes and edges, as visualized in Figure 14.

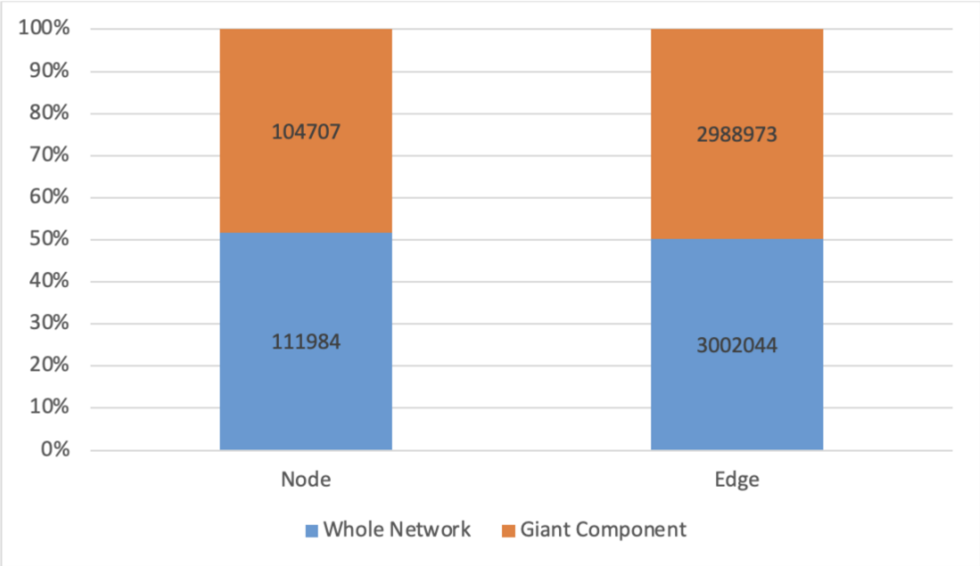

Fig.14. The Difference in the Number of Nodes and Edges in The Entire Network And Giant Component.

The giant component network consists of 104,707 nodes (accounting for 93.50% of the total) and 2,988,973 edges (representing 99.56% of the total edges). The discrepancy in edges is merely 13,071 (0.46%), and there is a variance of 7,277 (6.50%) nodes compared to the complete network. These slight differences indicate that the giant component comprehensively covers the majority of the entire network.

Among the total of 111,984 authors, the top five authors were chosen based on their degree distribution and clustering coefficient values. The author with the ID '7202492953' holds the highest degree among all these authors within the entire network. Subsequently, '7005197760' claims the second-highest degree, and '57195049611' secures the third position. For a comprehensive breakdown, please refer to Table 3. Remarkably, it's worth noting that the top five authors with the highest degrees all belong to the same community class.

Table 3. Top Five Most Degree

No	Author Id	Degree	Clustering Coefficient	Class
1.	7202492953	3.200	0.356936	713
2.	7005197760	3.194	0.39334	713
3.	57195049611	3.101	0.415891	713
4.	35398625000	3.080	0.4215	713
5.	57198904674	3.076	0.422595	713

In the largest community class, the author identified by the author ID '6506355194' holds the highest degree. This author stands out as having the highest degree within the five largest communities, as indicated in Table 4. Notably, the calculated graph density value amounts to 0.00047878. This value implies that there remains potential for

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

establishing additional relationships between authors within the network, indicating the possibility of further collaboration opportunities.

Table 4. Authors with The Most Degrees in the Top Five Class Communities

No	Author Id	Degree	Clustering Coefficient	Class
1.	6506355194	337	0.203988	291
2.	18041564100	339	0.092632	847
3.	6602604153	284	0.017469	176
4.	57205093001	270	0.019634	1213
5.	7801547112	246	0.109939	1049

C. Micro-Level Analysis

Authors with high betweenness centrality values are regarded as having significant intermediary roles within the network. Table 5 presents a compilation of the top five authors with the highest betweenness centrality, highlighting their prominent positions in facilitating connections and communication among various nodes within the network.

Table 5. Five Authors with the Most Betweeness Centrality

No	Author id	Degree	Betweenness Centrality	Class
1.	6602774565	554	104.519.134,7	1380
2.	30567573400	581	77.507.417,74	135
3.	6506944516	502	72.571.124,36	395
4.	14019972600	155	68.419.784,38	1213
5.	56483277100	165	63.329.922,03	1633

Based on the findings detailed in Table 5, the most influential author within this network is identified as '6602774565,' belonging to the 1380 community class. Notably, all authors with the highest betweenness centrality values originate from distinct communities, underscoring their unique roles as intermediaries. In terms of closeness centrality, authors with higher values can efficiently disseminate information across the network. The closeness centrality results for authors with the most degrees are outlined in Table 6, offering insights into their potential to efficiently share information within the network.

Table 6. Closeness Centrality of the Five Authors with the Most

No	Author id	Degree	Closeness Centrality	Class
1.	7202492953	3.200	0.209997	713
2.	7005197760	3.194	0.212637	713
3.	57195049611	3.101	0.210255	713
4.	35398625000	3.080	0.209607	713
5.	57198904674	3.076	0.209398	713

Eigenvector Centrality, also known as Eigen centrality, serves as a measure to assess an author's impact on the network. Table 7 presents the eigenvector centrality values for the top five authors with the highest degrees, shedding light on their influence within the co-authorship network.

Table 7. Eigenvector Centrality of the Five Authors with the Most Degrees

No	Author id	Degree	Eigenvector Centrality	Class
1.	7202492953	3200	0.950974	713
2.	7005197760	3194	1	713
3.	57195049611	3101	0.998588	713
4.	35398625000	3080	0.998389	713
5.	57198904674	3076	0.998357	713

4. CONCLUSION

A thorough examination of the co-authorship network revealed the complex web of collaborative relationships among authors from PTN-BH institutions. This analysis uncovered how these authors work together across various academic fields, shedding light on the key figures within the network who serve as central connectors and leaders in fostering scholarly partnerships. These influential authors not only play a pivotal role in the dissemination of knowledge but also drive research advancements and interdisciplinary collaboration, thereby shaping the direction and impact of academic work within the PTN-BH community.

REFERENCES

Abramo, G., D’Angelo, C. A., Di Costa, F., & Solazzi, M. (2011). The role of information asymmetry in the market for university-industry research collaboration. *Journal of Technology Transfer*, *36*(1), 84–100. https://doi.org/10.1007/s10961-009-9131-5

Aggrawal, N., & Arora, A. (n.d.). *Visualization, Analysis and Structural Pattern Infusion of DBLP Co-Authorship Network Using Gephi*.

Bayu, A., Nandiyanto, D., Kunta Biddinika, M., & Triawan, F. (2020). *How Bibliographic Dataset Portrays*. http://sinta2.ristekdikti.go.id/

Camacho, D., Panizo-LLedot, Á., Bello-Orgaz, G., Gonzalez-Pardo, A., & Cambria, E. (2020). The four dimensions of social network analysis: An overview of research methods, applications, and software tools. *Information Fusion*, *63*, 88–120. https://doi.org/10.1016/j.inffus.2020.05.009

Fagan, J., Eddens, K. S., Dolly, J., Vanderford, N. L., Weiss, H., & Levens, J. S. (2018). Assessing Research Collaboration through Co-authorship Network Analysis. *J Res Adm*, *49*(1), 76–99.

Farhan Bashir, M., Ma, B., Bilal, &, Komal, B., Muhammad, &, & Bashir, A. (n.d.). *Analysis of environmental taxes publications: a bibliometric and systematic literature review*. https://doi.org/10.1007/s11356-020-12123-x/Published

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

González-Alcaide, G., Pinargote, H., & Ramos, J. M. (2020). From cut-points to key players in co-authorship networks: a case study in ventilator-associated pneumonia research. *Scientometrics*, *123*(2), 707–733. https://doi.org/10.1007/s11192-020-03404-w

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. In *Computers and Education: Artificial Intelligence* (Vol. 1). Elsevier B.V. https://doi.org/10.1016/j.caeai.2020.100001

Kong, X., Mao, M., Jiang, H., Yu, S., & Wan, L. (2019). How does collaboration affect researchers' positions in co-authorship networks? *Journal of Informetrics*, *13*(3), 887–900. https://doi.org/10.1016/j.joi.2019.07.005

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

Kwilinski, A. (2023). THE RELATIONSHIP BETWEEN SUSTAINABLE DEVELOPMENT AND DIGITAL TRANSFORMATION: BIBLIOMETRIC ANALYSIS. In *Virtual Economics* (Vol. 6, Issue 3, pp. 56–69). Institute for International Cooperation Development. https://doi.org/10.34021/ve.2023.06.03(4)

Lang, D. J., Wiek, A., Bergmann, M., Stauffacher, M., Martens, P., Moll, P., Swilling, M., & Thomas, C. J. (2012). Transdisciplinary research in sustainability science: Practice, principles, and challenges. *Sustainability Science*, *7*(SUPPL. 1), 25–43. https://doi.org/10.1007/s11625-011-0149-x

Li, Y., & Huang, J. (2023). The evolution of collaborative networks: A social network analysis of Chinese environmental protection policy. *Public Policy and Administration*, *38*(1), 34–57. https://doi.org/10.1177/09520767211034664

Liu, X., Bollen, J., Nelson, M. L., & Van De Sompel, H. (2005). Co-authorship networks in the digital library research community. *Information Processing and Management*, *41*(6), 1462–1480. https://doi.org/10.1016/j.ipm.2005.03.012

Munoz, D. A., Queupil, J. P., & Fraser, P. (2016). Assessing collaboration networks in educational research: A co-authorship-based social network analysis approach. *International Journal of Educational Management*, *30*(3), 416–436. https://doi.org/10.1108/IJEM-11-2014-0154

Newman, M. E. J. (2006). Modularity and community structure in networks. *The Proceedings of the National Academy of Sciences* , *103*(23), 8577–8582. www.pnas.orgcgidoi10.1073pnas.0601602103

Phillips, M. E., Zavalina, O. L., & Tarver, H. (2019). Using Metadata Record Graphs to Understand Digital Library Metadata. *Proceeding International Conference on Dublin Core and Metadata Applications*, 49–58. https://texashistory.unt.edu/

Savić, M., Ivanović, M., Radovanović, M., Ognjanović, Z., Pejović, A., & Krüger, T. J. (2015). Exploratory Analysis of Communities in Co-authorship Networks: A Case Study. *Advances in Intelligent Systems and Computing*, *311*, 55–64. https://doi.org/10.1007/978-3-319-09879-1_6

Si, Y. (2022). Co-authorship in energy justice studies: Assessing research collaboration through social network analysis and topic modeling. In *Energy Strategy Reviews* (Vol. 41). Elsevier Ltd. https://doi.org/10.1016/j.esr.2022.100859

Silva, F. G. M., Quoc, ·, Nguyen, T., Correia, A. F. P. P., Clemente, F. M., Manuel, F., & Martins, L. (n.d.). *Ultimate Performance Analysis Tool (uPATO) Implementation of*

Network Measures Based on Adjacency Matrices for Team Sports 123. http://www.springer.com/series/8884

Soria Mateo, by, Kim, J., & Professor, A. (2013). *Analysis and Visualization of Co-Authorship Network in Life Cycle Assessment Research Area: A case study of the International Journal of Life Cycle Assessment*.

Stieglitz, S., Dang-Xuan, L., Bruns, A., & Neuberger, C. (2014). Socialmedia analytics. *Business and Information Systems Engineering*, *6*(2), 89–96. https://doi.org/10.1007/s12599-014-0315-7

Sun, Y., Zhang, C., & Kok, R. A. W. (2020). The role of research outcome quality in the relationship between university research collaboration and technology transfer: empirical results from China. *Scientometrics*, *122*(2), 1003–1026. https://doi.org/10.1007/s11192-019-03330-6

Thanoon, K. H., Sultan, N. A., Mahmood, B., & Kadhim, D. S. (2021). Measuring scientific collaboration in co-authorship networks. *IAES International Journal of Artificial Intelligence*, *10*(4), 1103–1114. https://doi.org/10.11591/IJAI.V10.I4.PP1103-1114

Umadevi, V. (2013). CASE STUDY-CENTRALITY MEASURE ANALYSIS ON CO-AUTHORSHIP NETWORK. In *Journal of Global Research in Computer Science* (Vol. 4, Issue 1). www.jgrcs.info

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)