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A Network Analysis Approach to Comparing Collaboration Among Researchers at Universiti Putra Malaysia

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ABSTRACT

This study aims to analyze research collaboration within the Department of Mathematics and Statistics in Universiti Putra Malaysia in two distinct periods: 2020–2021 and 2022–2023. The analysis employs social network analysis and graph theory concepts, focusing on centrality measures such as degree, closeness, betweenness, and eigenvector centralities. This study investigates changes in research collaboration between the two periods in terms of centrality measures and identifies factors that influence their values.This study investigates three main research questions. First, it examines how to effectively model research collaborations among mathematicians. Second, it explores how centrality measures in collaboration networks, such as degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality, can be used to predict the most influential mathematicians. Finally, it analyzes changes in collaboration networks between 2020–2021 and 2022–2023. The findings may offer insights into enhancing future collaborative strategies and fostering a more connected and productive research environment.

Keywords: centrality measure, collaboration graph, network analysis, ranking

1 INTRODUCTION

Graph theory [1] is a branch of mathematics that focuses on the study of graphs, which are mathematical structures that represent pairwise relationships between objects. One widely used application of graph theory is social network analysis [2, 3], a method for examining social structures through the principles of network and graph theories. It also serves as a powerful tool for modeling various real-world problems, including cryptography [4], robotics [5], community-based problem solving [6–8] and pattern recognition [9].

A *graph* $G = (V, E)$ consists of a nonempty finite set V of *vertices* (or *nodes*) and a set E of *edges* (or *links* or *lines*) that connect pairs of vertices [10]. In some cases, it is useful to denote the vertex and edge sets of G as $V(G)$ and $E(G)$, respectively, to avoid ambiguity. In undirected graphs, connections between two vertices are mutual, meaning the edges do not have a specific direction–each edge simply links two vertices. In contrast, directed graphs (or digraphs) [11] feature edges with a defined direction, indicating a one-way relationship from one vertex to another.

Several studies have applied network analysis techniques to examine collaboration and influence across various domains. Razak et al. [12] investigated research collaboration among 38 lecturers at Universiti Kebangsaan Malaysia from 2012–2014 using social network analysis and graph theory, analyzing metrics such as degree, closeness, and betweenness centrality. Similarly, Zu and Yow [13] studied 44 researchers at Universiti Putra Malaysia, revealing an increase in research collaborations from 80 (2015–2017) to 133 (2018–2020) and identifying key researchers based on degree centrality using Gephi [14]. In social media analysis, Tan [15] identified social media influencers in the Twitter community by comparing four centrality measures, with eigenvector centrality proving most effective. Network analysis also plays a role in sports [16], which used Gephi and the HITS algorithm to evaluate player significance in volleyball. Additionally, Liang et al. [17] examined interaction patterns in research-practice partnerships, demonstrating how centrality measures reflect participant influence and collaboration. Colladon et al. [18] analyzed gasoline prices in relation to gas stations' network positions using Spearman's correlation, linking centrality metrics to pricing strategies. These studies highlight the versatility of network analysis in understanding collaboration, influence, and connectivity across different fields.

This study builds upon the work presented in [13] by examining the social structure of 42 mathematicians at Universiti Putra Malaysia. In this analysis, researchers are modeled as vertices and their research collaborations as edges. The main goal is to assess several centrality measures—specifically, degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality—within the collaboration networks. We explore the structural dynamics of these networks across two time periods: 2020–2021 and 2022–2023. Furthermore, we analyze the networks generated based on each centrality measure.

2 METHODOLOGY

A survey involving 42 researchers from the Department of Mathematics and Statistics at Universiti Putra Malaysia was carried out using online databases namely Scopus and Google Scholar. The gathered data were initially organized in a spreadsheet and subsequently converted into matrix form for the periods 2020–2021 and 2022–2023. To ensure accuracy, we cross-verify the publication records using multiple sources and use author IDs where available. In addition, we include only publications for authors affiliated with the department during the period of interest. We then conduct a manual review to resolve any ambiguous or borderline cases.

In this study, we construct graphs comprising 42 vertices and their corresponding edges, where each vertex represents a researcher and each edge denotes a research collaboration. Consequently, the adjacency matrix is of dimension 42×42. Each researcher is assigned a unique numerical identifier (ID). To identify collaborations, we check for co-authorship in published papers—if two researchers have co-authored a paper, a value of 1 is assigned in the corresponding cell of the adjacency matrix; otherwise, a value of 0 is recorded.

2.1 Graph Construction

To construct the collaboration network, we begin by importing two spreadsheets Files A and B into Gephi. File A contains columns for ID and label, corresponding to each researcher's unique identifier and name, respectively. File B includes source and target columns that represent collaborations between researchers through their IDs. Both files are imported into the same Gephi workspace, with File A designated as the "Nodes table" and File B as the "Edges table" to preserve data consistency. An undirected graph type is selected for the analysis.

Once the network is constructed, vertex positions are adjusted to enhance clarity and visual presentation. Subsequently, key network metrics—such as degree, network diameter, and eigenvector centrality—are computed to extract insights into the collaboration patterns among the researchers.

2.2 Network Analysis Measure

In this study, we examine the collaboration network using four centrality measures [13, 19]: degree, betweenness, closeness and eigenvector.

Let G be a graph, $u, v \in V(G)$ and $u \neq v$. Each centrality measure is first defined as below.

Definition 2.1 *The* degree centrality *of a vertex u is defined as the number of edges that are incident to u.*

Definition 2.2 *The* closeness centrality *of a vertex u is defined as the average distance from u to all other vertices v in G, as below:*

$$C(u) = \frac{1}{\sum_v d_{u,v}} \tag{1}$$

where $d_{u,v}$ is the distance from u to v.

Definition 2.3 *The* betweenness centrality *of a vertex u measures how frequent u appears on the shortest paths between two other vertices s and t in G, defined as:*

$$B(u) = \sum_{s,t \in V} \frac{\sigma_{st}(u)}{\sigma_{st}} \tag{2}$$

where σ_{st} denotes the total number of shortest paths between s and t, and $\sigma_{st}(u)$ denotes the number of shortest paths between s and t that pass through u.

Definition 2.4 *The* eigenvector centrality *of a vertex u measures the influence of u within a graph. Let $A = (a_{u,v})$ be the adjacency matrix of G and $u, v \in V$. The eigenvector centrality of u is given by:*

$$x_u = \frac{1}{\lambda} \sum_{v \in M_u} x_v = \frac{1}{\lambda} \sum_{v \in G} a_{u,v} x_v \tag{3}$$

where λ is a constant and $M(u)$ represents the set of neighbors of u. In matrix notation, we have

$$Ax = \lambda x \tag{4}$$

where x is an eigenvector of A and λ is its largest associated eigenvalue.

3 RESULTS AND DISCUSSION

This section presents the findings of this study. We first present the total number of collaborations and individual researcher contributions for the periods 2020–2021 and 2022–2023. We then focus on the analysis of graphs using various centrality measures, by discussing and examining tables listing the top 10 vertices ranked by each centrality measure for both time periods.

Overall, there is an increasing trend in research collaborations across the two periods, with the total number rising from 73 in 2020–2021 to 87 in 2022–2023. A detailed breakdown of the number of collaborations for each researcher during the two periods is shown in Figure 1. We can see that 22 researchers increased their number of collaborations in the second period compared to the first. For example, Researcher 2 collaborated with 9 individuals in 2020–2021 and 12 in 2022–2023. In contrast, 12 researchers experienced a decrease in collaborations; for instance, Researcher 19's collaborations dropped from 5 to just 1. Overall, approximately 52.5% of researchers increased their collaborations, 28.5% saw a decrease, and 19% remained unchanged. This indicates that the number of collaborations varied between the two periods, 2020–2021 and 2022–2023.

3.1 Graph Analysis

Next, we analyze the top 10 researchers with the highest values for each centrality measure in the respective periods. These centrality values were computed using Gephi. After obtaining the results, we sorted the values in descending order to identify the top 10 researchers, aiming to determine the most influential individuals within the network. Tables 1 and 2 show that some researchers share identical values, particularly in degree centrality. This indicates that these researchers have the same number of collaborators during the given time frame.

Table 1 : Top 10 vertices by centrality measure in 2020–2021

	Degree		**Closeness**		**Betweenness**		**Eigenvector**	
Rank	ID	Value	ID	Value	ID	Value	ID	Value
1	9	11	6	0.456790	4	205.0630	9	1.0000
2	2, 6	9	25	0.430233	8	183.4833	2	0.8950
3	4, 34	8	4	0.425287	6	183.1294	6	0.8343
4	25	7	9	0.415730	25	129.4508	25	0.7285
5	38	6	2	0.397849	34	119.5619	4	0.6819
6	10, 41, 40, 19, 17	5	17	0.389474	9	119.0464	40	0.6184
7	20, 33, 13, 8, 30, 15	4	38	0.385417	2	80.1127	17	0.5915
8	1, 42, 3, 37, 11	3	40	0.381433	15	78.9270	38	0.5704
9	14, 22, 26, 27, 39, 12, 21, 18, 36	2	15	0.362745	19, 26	70.0000	41	0.5391
10	24, 5, 29, 7, 16, 28	1	19	0.359223	10	59.5499	33	0.5122

The graphs for the two periods, 2020–2021 and 2022–2023, based on centrality measures are presented below. In these visualizations, the size and color of each vertex represent the degree values—larger sizes and darker colors indicate higher centrality values.

Degree Centrality In the context of research collaboration, degree centrality is defined by the number of collaborators a researcher has. Thus, degree centrality is directly proportional to the number of collaborators: the more collaborators a researcher has, the higher their degree centrality. The graphs that visualize the degree centrality for the two periods are shown in Figure 2. In Figure 2a, Vertex 9 appears as the largest and darkest node in the network, indicating the highest degree centrality. It is connected to 11 edges, which means that Researcher 9 had 11 collaborators during this period.

Similarly, in Figure 2b, Vertex 2 and Vertex 34 are the largest and darkest nodes, signifying that both Researchers 2 and 34 share the highest degree centrality in 2022–2023, each with 12

ID	2020-2021	2022-2023
1	3	4
2	9	12
3	3	4
4	7	4
5	1	2
6	9	4
7	1	2
8	4	4
9	11	8
10	5	4
11	3	1
12	2	0
13	4	7
14	2	2
15	4	10
16	1	5
17	5	5
18	2	4
19	5	1
20	4	10
21	2	1
22	2	7
23	0	1
24	1	3
25	7	5
26	2	2
27	2	4
28	1	1
29	1	3
30	4	4
31	0	2
32	0	0
33	4	6
34	8	12
35	0	0
36	2	8
37	3	6
38	6	2
39	2	0
40	5	4
41	5	6
42	3	4

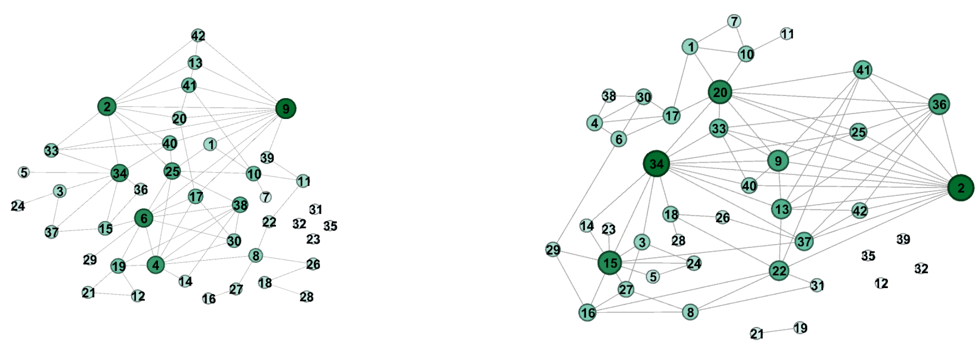
Figure 1 : Number of collaboration for each researcher in 2020–2021 and 2022–2023

collaborators. However, two vertices–Vertices 32 and 35–remain isolated in the network. This may be due to collaborations with researchers from other universities or their absence from the department during the observed periods. Both vertices have a degree centrality of 0, indicating that these researchers had no collaborations within the department in either period.

Closeness Centrality Based on Figure 3a, Vertices 4, 6, and 25 have the darkest colors and largest sizes, indicating that they possess the highest closeness centrality among all vertices. Consequently, these vertices occupy the most central positions within the network. In other words, these researchers occupy advantageous positions within the department, making them key figures to whom others can turn for important information or resources related to their area of expertise. On the other

Table 2 : Top 10 vertices by centrality measure in 2022–2023

	Degree		**Closeness**		**Betweenness**		**Eigenvector**	
Rank	ID	Value	ID	Value	ID	Value	ID	Value
1	2, 34	12	34	0.522388	20	186.6509	2	1.0000
2	20, 15	10	20	0.492958	34	167.4273	34	0.8810
3	9, 36	8	2	0.492958	15	140.3006	20	0.7804
4	13, 22	7	15	0.472973	17	80.7238	9	0.7583
5	41, 33, 37, 27	6	9	0.443038	22	69.2337	36	0.6964
6	17, 25, 16	5	33	0.432099	2	58.9608	13	0.6493
7	1, 10, 40, 42, 3, 4, 6, 30, 8, 18	4	29	47.5619	2	80.1127	33	0.6251
8	24, 29, 23	3	36	0.426829	10	46.9286	41	0.5898
9	7, 38, 5, 14, 26, 31	2	37	0.426829	18	44.01667	25	0.5644
10	11, 28, 19, 21	1	22	0.421687	37	42.8604	37	0.4833



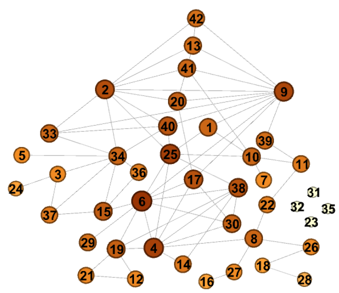
(a) 2020–2021 (b) 2022–2023

Figure 2 : Graphs illustrating degree centrality in research collaborations for the two periods

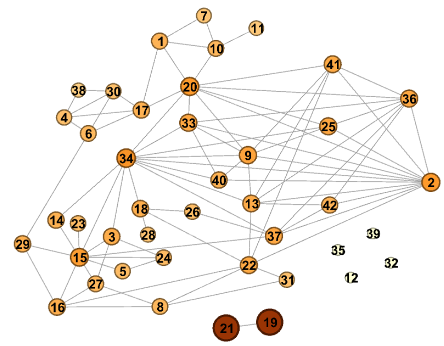
hand, the isolated vertices, characterized by the lightest colors and smallest sizes, lack connections to other nodes. As a result, they have no closeness centrality value and are unable to effectively disseminate information across the department.

The network shown in Figure 3b represents the closeness centrality of research collaborations during the second period, spanning from 2022 to 2023. In the graph, Vertices 19 and 21 stand out as the darkest and largest, indicating their highest closeness centrality—though this is due to their exclusive connection to each other. However, when considering the broader structure of the network, Vertices 2, 20 and 34 exhibit higher closeness centrality values compared to others. These vertices are the most effective in facilitating knowledge dissemination within the department during this period.

Betweenness Centrality By analyzing Figure 4a in terms of betweenness centrality, it is evident that Researchers 4, 6 and 8 are marked with the darkest colors, highlighting their significant roles as central intermediaries within the research collaboration network during the first period. These individuals serve as crucial connectors between different groups or researchers, helping to maintain the network's structural cohesion and facilitating the flow of collaborative efforts across the entire



(a) 2020–2021

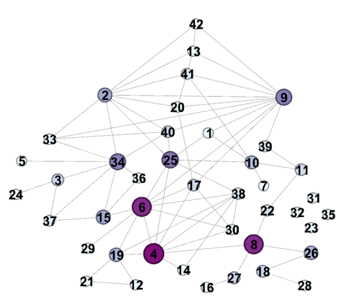


(b) 2022–2023

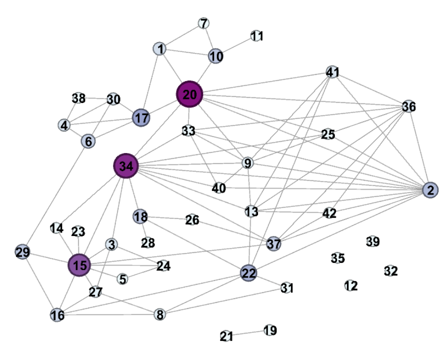
Figure 3 : Graphs illustrating closeness centrality in research collaborations for the two periods

network.

For the second period, Researchers 15, 20 and 34 exhibit the highest betweenness centrality, as evidenced by the darkest colors of their vertices in Figure 4b. Among them, Researcher 20 with the darkest shade has the greatest influence on the flow of the network and acts as a crucial bridge connecting multiple groups. The isolated vertices in the network, such as Vertices 12, 32, 35 and 39, are disconnected from the rest of the network and exhibit no betweenness centrality. These vertices represent researchers who do not participate in collaborations within the department. The lack of connectivity for these researchers suggests missed opportunities for knowledge sharing and involvement in group research projects, potentially limiting their impact and participation in the department's academic activities.



(a) 2020–2021

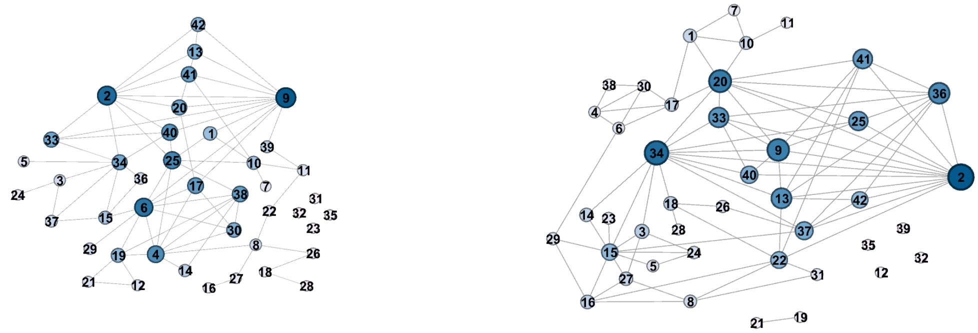


(b) 2022–2023

Figure 4 : Graphs illustrating betweenness centrality in research collaborations for the two periods

Eigenvector Centrality Lastly, Figure 5a presents the eigenvector centrality of research collaborations, where both the size and color of the vertices represent their centrality values. Vertices 2, 6 and 9 appear larger and darker, identifying them as the top three researchers with the highest eigenvector centrality. Notably, Vertex 9 stands out the most, underscoring its pivotal role in collaboration and knowledge dissemination by being connected to other highly central researchers within the network. This aligns with the concept of eigenvector centrality, which measures a vertex's influence based not only on the number of its connections but also on the importance of the vertices it is connected to. A vertex that is linked to many highly influential vertices will itself have a high eigenvector centrality. In the context of research collaboration, researchers connected to such central figures gain greater visibility and are better positioned to shape the research direction within the department.

On the other hand, Figure 5b illustrates eigenvector centrality for research collaborations in 2022–2023, where Vertices 2, 20 and 34 exhibit the highest eigenvector centrality. Vertex 2 stands out as the most prominent vertex in the network, as indicated by its large size and dark color. Its strong connections to other highly central nodes further enhance its crucial role within the network, reinforcing its influence and importance in the overall structure.



(a) 2020–2021

(b) 2022–2023

Figure 5 : Graphs illustrating eigenvector centrality in research collaborations for the two periods

4 CONCLUSION

This study offers an in-depth analysis of research collaboration among mathematicians at Universiti Putra Malaysia across two periods: 2020–2021 and 2022–2023. Employing graph theory and social network analysis, we explored the structure of collaboration networks, identified influential researchers, and observe changes in network dynamics. The results reveal a general rise in collaborative efforts, with several key researchers maintaining or enhancing their central positions within the network. The study highlights the importance of degree, closeness, betweenness and eigenvector centralities as indicators of a researcher's influence and connectivity. The observed increase in collaboration during the second period reflects a more vibrant and effective research environment within the department.

Future research could expand the analysis time frame to capture long-term trends and the evolution of collaboration patterns among researchers. Additionally, conducting similar studies across multiple universities would offer deeper insights into how research collaboration dynamics vary across different academic settings. Exploring interdisciplinary collaborations between mathematicians and researchers from other fields could also shed light on the challenges and advantages of multidisciplinary research, while offering strategies to enhance the effectiveness of such partnerships. Building on the findings of this study, future work in these areas could significantly advance our understanding of academic collaboration networks and their impact on research productivity and innovation.

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REFERENCES

[1] A. Majeed and I. Rauf, "Graph theory: A comprehensive survey about graph theory applications in computer science and social networks," *Inventions*, vol. 5, no. 1, p. 10, 2020.

[2] J. Scott, *Social Network Analysis: Research Methods.* Bloomsbury Publishing, 2024.

[3] S. S. Singh, S. Muhuri, S. Mishra, D. S. andH. K. Shakya, and N. Kumar, "Social network analysis: A survey on process, tools, and application," *ACM Computing Surveys*, vol. 56, no. 8, pp. 1–39, 2021, doi:10.1145/3648470.

[4] P. L. K. Priyadarsini, "A survey on some applications of graph theory in cryptography," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 18, no. 3, pp. 209–217, 2015.

[5] L. W. Tsai and J. J. Lee, "Kinematic analysis of tendon-driven robotic mechanisms using graph theory," 1989.

[6] K. S. Yow and S. Luo, "Learning-based approaches for graph problems: A survey," *Preprint*, 2022, arXiv:2204.01057v2.

[7] K. S. Yow, N. Liao, S. Luo, R. Cheng, C. Ma, and X. Han, "A survey on machine learning solutions for graph pattern extraction," *Preprint*, 2023, arXiv:2204.01057v3.

[8] K. S. Yow, N. Liao, S. Luo, and R. Cheng, "Machine learning for subgraph extraction: Methods, applications and challenges," *Proc. VLDB Endow*, vol. 16, no. 12, pp. 3864–3867, 2023, doi:10.14778/3611540.3611571.

[9] A. dos Santos Siqueira, C. E. B. Junior, W. E. Comfort, L. A. Rohde, and J. R. Sato, "Abnormal functional resting-state networks in adhd: graph theory and pattern recognition analysis of fmri data," *BioMed Research International*, 2014.

[10] G. Chartrand and P. Zhang, *A first course in graph theory.* Courier Corporation, 2013.

[11] K. S. Yow, K. J. Morgan, and G. E. Farr, "Factorisation of greedoid polynomials of rooted digraphs," *Graphs and Combinatorics*, vol. 37, no. 6, pp. 2245–2264, 2021, doi:10.1007/s00373-021-02347-0.

[12] F. A. Razak, F. A. Shahabuddin, and N. S. N. Zamri, "Analyzing research collaborations within the School of Mathematical Sciences, UKM using Graph Theory," in *Journal of Physics: Conference Series*, vol. 1212, no. 1, 2019, p. 012033.

[13] U. S. Zu and K. S. Yow, "An analysis on research collaboration between math-

ematicians in Universiti Putra Malaysia," *ASM Science Journal*, vol. 19, 2024, doi:10.32802/asmscj.2023.1485.

[14] M. Bastian, S. Heymann, and M. Jacomy, "Gephi: An open source software for exploring and manipulating networks," *International AAAI Conference on Weblogs and Social Media*, vol. 3, no. 1, pp. 361–362, 2009.

[15] W. Tan, "A study on the centrality measures to determine social media influencers of food-beverage products in twitter," *The Journal of The Institution of Engineers, Malaysia*, vol. 82, 2022.

[16] S. Iermakov, T. Yermakova, and K. Wnorowski, "Statistical match reports of the 2022 volleyball world championship in the context of network analysis with gephi," *Physical Culture, Recreation and Rehabilitation*, vol. 2, pp. 44–59, 2023.

[17] H. Liang, C. Qi, R. Huang, H. Zuo, and J. He, "Mathematics teachers' interaction patterns and role changes in online research-practice partnerships: A social network analysis," *Computers & Education*, vol. 218, p. 105077, 2024.

[18] A. F. Colladon, G. Verdoliva, L. Segneri, and A. G. Vitali, "Analyzing gasoline prices in five italian cities: Insights from social network analysis," *Cities*, vol. 150, p. 105075, 2024.

[19] S. Peng, Y. Zhou, L. Cao, S. Yu, J. Niu, and W. Jia, "Influence analysis in social networks: A survey," *Journal of Network and Computer Applications*, vol. 106, pp. 17–32, 2018.