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Review Article

A review of network analysis studies on psychopathology from the perspective of co-authorship network analysis

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Abstract

One area of growing interest in computational psychology is the analysis of psychopathological networks. Numerous related studies and several recent review articles have been published in this field. Understanding the characteristics, authors, relationships, and focus areas of the studies can provide greater benefits to researchers in this field. This article presents the first analysis of co-authorship networks in computational network-oriented psychopathology research. To this end, bibliographic data were collected from Google Scholar. Given the difficulty and potential for errors in manually reviewing the 2,799 research articles published between 2000 and 2022, co-authorship network analysis was conducted using machine learning methods for graph analysis. Network density, average degree, clustering coefficient, and the number of communities were calculated, and temporal changes were evaluated. Prominent authors were identified based on centrality measures. The co-authorship network for the entire period consisted of 6,025 nodes and 9,808 weighted edges. Time series analysis showed a linear correlation between the number of authors and the number of connections. Furthermore, the number of communities was linearly correlated with the number of authors. Identifying research clusters through topic modeling revealed that keywords such as user, event, family, and comments were the most commonly used representative texts in articles in this field. Additionally, we highlighted disorders that may have potential for more research in the field of network analysis, those with no related publications, for further investigation. Finally, the findings show a lack of collaboration between computer science researchers and specialists in this area.

Keywords

Psychopathology networks
Bibliometric analysis
Co-authorship analysis
Topic modeling

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Introduction

Psychopathological disorders, also known as mental disorders, encompass a broad range of conditions characterized by abnormal thoughts, feelings, and behaviors. These disorders are typically categorized into several major types according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5-TR), a widely accepted classification system developed by the American Psychiatric Association. Major categories include anxiety disorders, mood disorders (such as depression and bipolar disorder), psychotic disorders (including schizophrenia), personality disorders, eating disorders, trauma-related disorders (like post-traumatic stress disorder), and substance abuse disorders. Each category has specific criteria for diagnosis, often involving distress and impairment in daily functioning (American Psychiatric Association, 2022).

The use of computer methods and machine learning in psychological research has become increasingly prevalent (Jacobucci & Grimm, 2020). These studies can greatly aid the development and advancement of fields such as psychopathology. For example, network analysis has emerged as a crucial tool in psychopathology research, providing a novel perspective on the complex interplay of symptoms and their dynamic relationships (Contreras et al., 2019). This approach allows researchers to visualize and quantify the intricate web of interactions among symptoms, thereby offering a more nuanced understanding of mental disorders. It can help identify central symptoms or 'nodes' that may play a significant role in the onset, maintenance, or exacerbation of a disorder, which could be targeted in treatment.

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However, while the application of network analysis in psychopathology has been extensively studied, less attention has been given to the examination of the research field itself through the lens of study collaboration patterns, identify key players, map research communities, quantify impact, and identify interdisciplinary opportunities. Co-authorship network analysis, is itself a specific type of network analysis that offers a unique perspective to understand the collaborative patterns and intellectual structure of a scientific field. It allows for the exploration of how researchers collaborate, how research clusters are formed, and how knowledge is disseminated within a field. It can also reveal the strengths and weaknesses of the collection of published works in that scientific field and identify areas suitable for activity and development (Kong et al., 2019)**.**

Given the abundance of co-authorship research conducted in the field of network analysis for psychological pathology, a gap in the literature exists regarding knowledge of the characteristics and collective set of these studies from various perspectives. The aim of this article is to address this research gap. Additionally, strengthening the findings of co-authorship network analysis in psychological pathology research using machine learning techniques is a secondary objective of this study. Therefore, based on our knowledge, we will be addressing co-authorship network analysis for the first time in the field of computational psychology.

The following article will begin with a general overview of recent literature in the field of psychological network analysis, focusing on its key features.

Given that the proposed network analysis will be enhanced by machine learning algorithms and text processing, section 1.2 will succinctly address the computational prerequisites of this study. Chapter 3 will discuss data collection and present the corresponding prism plot, while chapter 4 will describe an improved version based on machine learning as the research method in a diagram. Chapter 5 will provide a step-by-step analysis of the results, including various visual tools and perspectives. Finally, chapter 6 will conclude with a summary and potential future research directions.

Review of Literature

Psychopathology refers to the study of mental disorders, their causes, and associated behaviors in individuals. This field of research seeks to understand the nature and origin of mental disorders, as well as their symptoms and related behaviors. Psychopathology utilizes various theories and disciplines such as psychology, psychiatry, neuroscience, and sociology to develop a comprehensive understanding of mental illnesses. This area of study is essential for identifying, diagnosing, and treating mental disorders, playing a crucial role in improving the lives of individuals affected by these conditions. Understanding psychopathology is vital for anyone interested in the field of mental health since it provides a foundation for comprehending the complex and layered nature of mental disorders (Mansager & Garrison, 2022). According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5-TR), there are 19 categories of mental disorders, which can be observed in Figure 1 (American Psychiatric Association,2022).

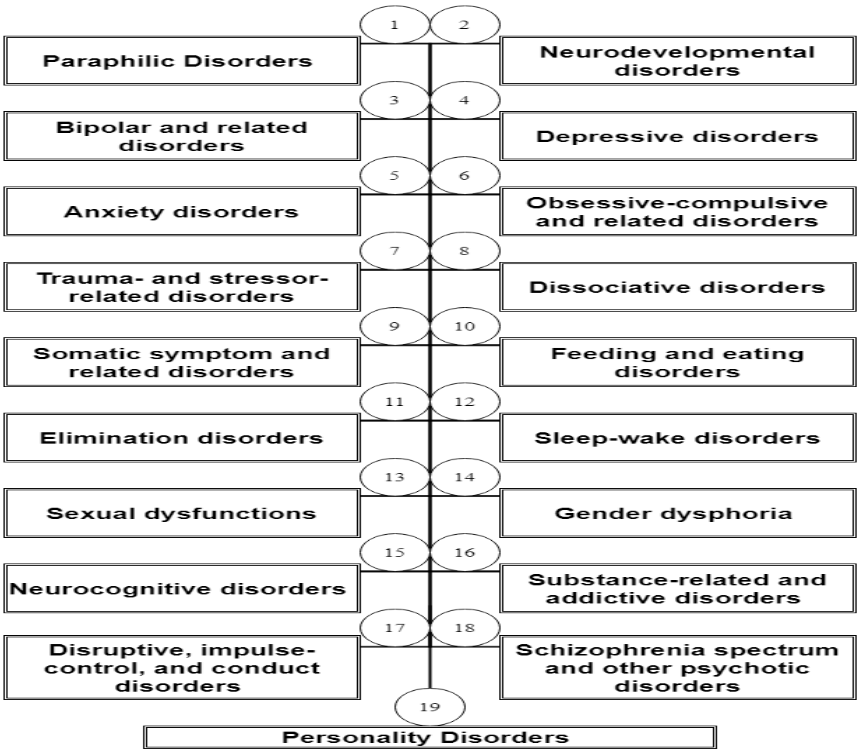

Figure 1. Classification system for mental disorders

Network analysis is a method used in the field of psychopathology to investigate the relationships between factors that are influential and relevant to mental illnesses. This analysis examines the patterns of interactions between entities or symptoms to gain insight into how they function in the formation or persistence of psychological disorders. As such, network analysis facilitates a better understanding of the mechanisms and causes that contribute to mental illnesses for researchers and those interested in the field of Psychopathology. Additionally, network analysis can be used to identify key individuals or groups within a specific community for control, monitoring, prevention, or therapeutic interventions (Mcnally, 2021).
In the field of Psychopathology, due to the large number of articles related to network analysis, several review studies have been published. One important article in this area is Contreras et al.'s (2019) systematic review of empirical research (using clinical data) that has used network analysis to study psychopathology. In this study, the strengths and weaknesses of the network analysis approach in clinical psychology has examined. The main objective of this research is to provide a summary of network studies in the field of Psychopathology with an emphasis on their main features, including sample type and characteristics, tools used to assess psychological variables or nodes, and network type. Finally, it concluded that due to uncertainties regarding the clinical application of network analysis, caution should be exercised in this area.

The relevant and important research belongs to Rubinov and colleagues (Robinaugh et al., 2020). In this article, a comprehensive review and critical analysis of 363 articles over two decades has been conducted. In the first decade of this research, the focus is on key contributions, methodology, and empirical studies. Additionally, in the following decade, attention is devoted to network approaches and vital avenues for future research in each of these areas were proposed. This research has two main objectives: (a) identifying strong phenomena and (b) developing formal theories to explain them. To achieve these objectives, researchers propose specific steps and believe that if these steps are followed, knowledge can be generated about the functioning of psychological disorders as causal systems.

The latest review study specifically focused on depression and is attributed to Wichers et al. (2021). In this validity review, the literature on network studies in the field of depression has been summarized. Four distinct methodological network approaches have been identified: (1) studies focused on symptoms at a macro level, (2) studies focused on momentary states at a micro level, (3) cross-sectional studies, and (4) dynamic time series data. Based on this, fifty-six studies have been identified and it has been found that different methodological network approaches to the network theory yield largely contradictory findings regarding depression. To aid future research in this area, the authors have proposed a new complementary network theory, the momentary impact dynamics network theory, to understand the progression of depression. Additionally, guidelines for future research have been provided and the potential use of networks in clinical practice has been discussed.

Computational prerequisites

Given the network analysis of co-authorship for Psychopathology and the enhancement of its results using machine learning techniques, there is a need for a quick and simple review of essential computational concepts. The necessary concepts for this article are briefly presented in a table, avoiding mathematical formulas and instead providing credible sources for further study.

Table 1. Review of Computational Prerequisite Concepts

Row	Concept	Description	Reference
1	Node	Each node in a co-authorship network represents an author who is connected to other nodes.	**(E Fonseca et al., 2016)**
2	Edge	An edge represents the collaboration between two authors or colleagues in writing an article. In other words, each edge between two authors indicates their collaboration in writing the article.	**(E Fonseca et al., 2016)**
3	Co-Authorship network	Connections formed by linking authors with joint authorship form a co-authorship network.	**(Kumar, 2015)**
4	Clustering Coefficient	The clustering coefficient in a network refers to the density of connections among neighbors of a node or vertex. In other words, if all neighbors of a node are connected, the clustering coefficient for that node is 1, and if none are connected, it is 0. The clustering coefficient for a network is equal to the average of all nodes' clustering coefficients.	**(Yang et al., 2016)**
5	Small-world Networks	A model of a network that has many real-world applications and its main feature is that from any node in the network, one can reach another node by passing through a small number of nodes (less than 6). Such networks have high clustering coefficients.	**(Khouzani & Sulaimany, 2022)**
6	Transitivity	In a network, if we have an edge from node A to node B and an edge from node B to node C, what percentage of cases will there be an edge from A to C in the network?	
7	Centrality	Centrality in a network is used for scoring and determining the importance of nodes. This can be done in various ways, which is why different types of centralities can be defined. For example, degree centrality refers to considering the number of	**(Bringmann et al., 2019)**

		connections each node has as its centrality score. Other types of centralities include Betweenness centrality and Closeness centrality.	
8	Community Detection	Algorithms for finding dense clusters of connections in networks exist. One common method for detecting communities is the Louvain algorithm, which maximizes the modularity property - meaning that connections within a community are more strongly correlated than with other communities.	**(Mittal & Goel, 2023)**
9	LDA (Latent Dirichlet Allocation)	A common algorithm for topic modeling involves suggesting titles or topics for texts or documents based on a large corpus of text. It proposes a representative topic that dominates the text. To achieve the best results in this algorithm, network search is used.	**(Jelodar et al., 2019)**
10	Grid Search	A type of computer search that tests all possible scenarios to find the optimal set of answers. To find the optimal set of answers, a criterion called coherence is used.	**(Bergstra James & Bengio Yoshua, 2012)**

Data Collection

Data were collected from Google Scholar and through the Publish or Perish program, covering the period from 2000 to 2022. A search was conducted using the combination of the terms "Psychopathology" and "Network Analysis" as "Psychopathology 'network analysis'" in the keyword section, resulting in articles related to Psychopathology and network analysis. Due to software limitations in processing less than 1000 records per calculation, search intervals were divided into three parts and the results of each part were merged. The initial search yielded 2807 records, which were manually screened to remove articles with unknown author names or empty author names, as having author names is a requirement for finding co-authorship networks. Ultimately, 2799 journals met the entry criteria. The research process is illustrated in Figure 2 using a PRISMA diagram.

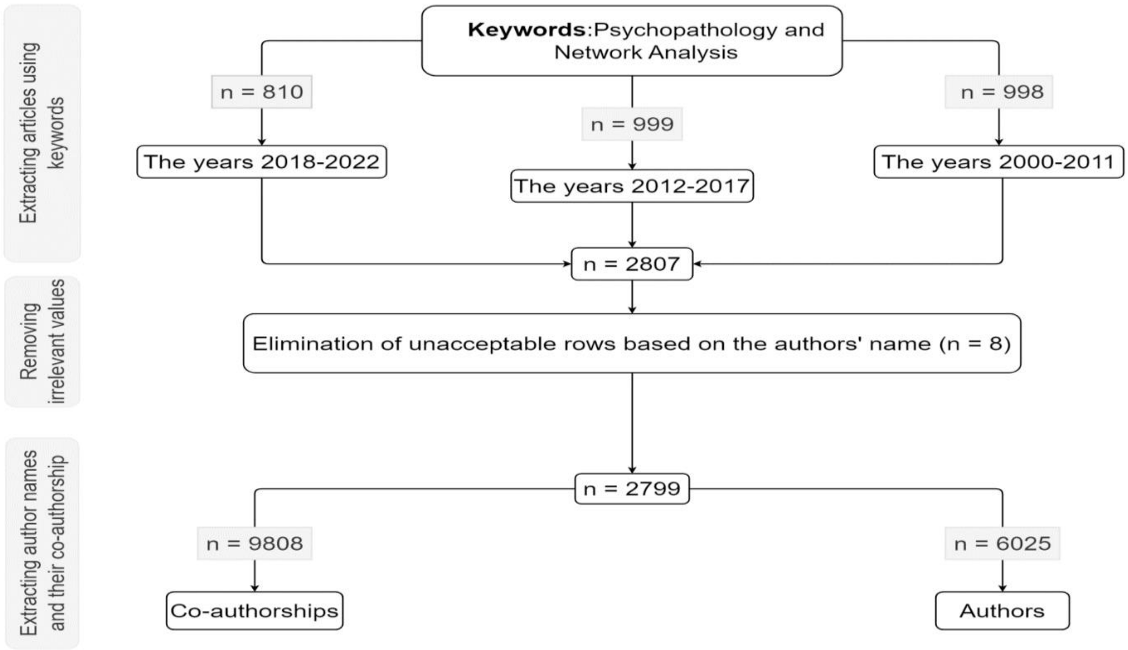

Figure 2. The PRISMA chart illustrates the trend of collecting articles under review

Method

The common method for conducting co-authorship network analysis is as follows (E Fonseca et al., 2016):
1. Retrieval of published scientific articles.
2. Pre-processing and standardization of collected data in terms of authors and their organizational affiliations.
3. Conducting network calculations and visualizing them.
4. Interpretation of results.

However, in case of a large number of articles, manual and individual review of them, in addition to being time-consuming, will also carry the risk of human error. Considering the large number of articles found in collecting relevant references and the machine learning methods for fast and accurate processing of bulk data, this research has utilized machine learning techniques to assist in more diverse and useful reviews. Thus, the research process will follow the stages shown in Figure 3. Implementation was done using Python programming language and its common libraries for each topic.

Figure 3. The general process of research

Following the creation of a network from extracted data based on the simultaneous presence of authors' names in each shared article, basic statistics of the network will be calculated, including the number of nodes and edges, as well as average degree, network density, transferability, and number of communities. These simple statistics can reveal the most prominent journals and authors in terms of frequency. After displaying the distribution of degrees and number of works for each year, the average shortest paths and number of connected nodes for the largest connected component at different time intervals will be calculated and plotted in two graphs. To evaluate whether an author has had an influential role in the network or not, three different centrality measures will be calculated: degree centrality, betweenness centrality, and closeness centrality.

Finally, the computational text analysis is conducted through topic modeling. In addition to descriptive network analysis, topic modeling is performed on abstracts using LDA. Firstly, numbers and punctuation marks are removed from each abstract and all letters are converted to lowercase. Then, English stop words that do not carry any meaning are also eliminated. Once each abstract is transformed into a bag of words, the textual data is formatted in a way that can be used as input for training the LDA model. In order to facilitate and expedite the process, all parameters in this method are kept as default except for the number of topics, which is set to 10. For this training, a model with 10 topics will be constructed, where each topic is a combination of keywords and each keyword gives a specific weight to the topic (Buchlak et al., 2020). Finally, the results will be analyzed using pyLDAvis, a Python library for interactive topic model visualization.

Results and Discussion

Understanding the diseases explored through social network analysis yields numerous valuable insights. Firstly, it allows us to gain knowledge about the prevalent mental disorders that have garnered significant attention. Secondly, by compiling a comprehensive catalogue of these disorders, we can identify those that have yet to receive adequate consideration. Exploring the underlying reasons for the neglect of such disorders may provide valuable insights for future research endeavors. Figure 4 presents an inventory of the mental illnesses that have been investigated using network analysis methodologies, highlighting that schizophrenia, personality disorders, and food and eating disorders have been the subject of extensive research efforts. Similarly, these disorders have great interests in general psychopathology researches (Rajaei et al., 2022; Sabri et al., 2021).

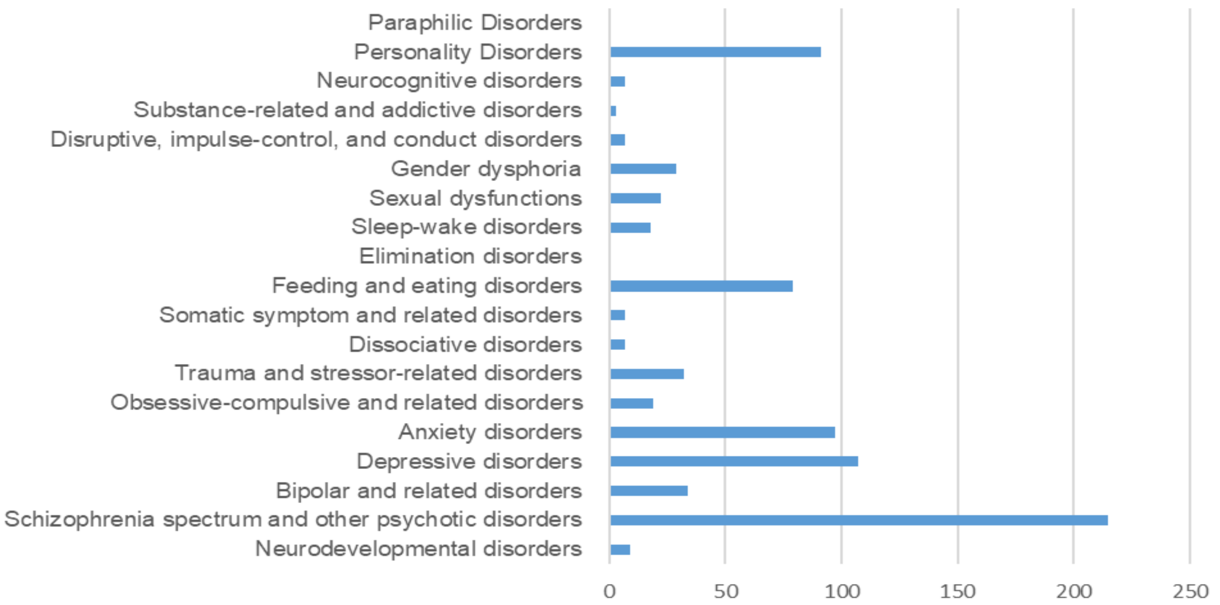

Figure 4. Distribution of mental illnesses investigated with network analysis

The creation of a network using the NetworkX library in the Python programming language was carried out[1]. Initial statistics such as the number of nodes (authors) and their connections, degree distribution (connections between each author and others), average degree, network density (communication density) over specific time periods, year of publication, number of discovered communities, etc. were prepared and visualized to provide initial understanding of the network of authors in scientific articles related to Psychopathology. The final result until late 2022 indicates 6025 authors and 9808 collaborations in this research field. The growth of the network is also depicted in Figure 3, showing an overall upward trend. Table 2 also shows that with an increase in the total number of publications, the average degree (number of joint collaborations) and number of discovered communities over time have increased while

1 https://www.osti.gov/biblio/960616

network density (total density) has decreased. These finding suggests a significant correlation between the quantity of publications and the level of collaboration among authors within the field. Furthermore, the analysis reveals a downward trend in overall collaboration per publication over time.

Table 2. Initial statistics from the data extracted for the co-authorship network of Psychopathology

Year of publication (since 2000)	Total number of publications	Nodes (authors)	Edges (collaborations)	Average Degree	Density	Transitivity	Identified communities
11	36	72	56	1.555	0.0219	1	35
2002	113	234	200	1709	0.0073	0.94405	108
2004	195	413	383	1.854	0.0045	0.91234	178
2006	294	614	602	1.96	0.0032	0.86257	257
2008	477	974	969	1.989	0.002	0.82578	402
2010	775	1613	1718	2.13	0.0013	0.80531	626
2012	1041	2235	2629	2.352	0.0011	0.77038	796
2014	1223	2689	3390	2.521	0.0009	0.73762	899
2016	1637	3653	5113	2.799	0.0008	0.65152	1100
2018	2008	4512	6615	2.932	0.0007	0.58798	1254
2020	2291	5090	7674	3.015	0.0006	0.54449	1324
2022	2720	6025	9809	3.256	0.0005	0.4779	1451

One interesting point to note in this area is the frequency of single-author articles and the maximum number of co-authors at the level of two or three individuals. In addition, although the overall trend in publications in this field is generally upward, the years 2017 and 2021 have seen the highest annual publication rates. At first glance and based on retrieved data, the top five journals in terms of number of relevant articles published over the past two decades were:

- Schizophrenia Bulletin
- American Journal of Psychiatry
- PLOS One
- Psychological Medicine
- Frontiers in Psychology

Additionally, the top five authors based on the number of published articles are as follows:

- Eiko Fried
- Richard J. McNally[2]
- Denny Borsboom[3]
- Yi Wang
- Sacha Epskamp

The footnote has been included for two authors due to their similar names in other scientific fields. The distribution of degrees (connections between authors) indicates that these degrees range from 0 to 67, with an average of 1.62, and degrees from 0 to 8 account for ninety-five percent of the degrees. This shows that the co-authorship network in the field of Psychopathology has a scale-free property, meaning that there are few authors with very high connections and many authors with low connections. The degree distribution graph of this network with such a property is almost similar to the graph in Figure 5A. While the number of publications per year shows some deficits in certain years, the trend of the overall number of publications is upward, Figure 5B.

Based on Figure 6A, there is a nearly perfect linear correlation between the number of authors and co-authorships (R2 = 0.9942, P <0.001). Additionally, the number of communities is linearly correlated with the number of authors (R2 = 0.9835, P <0.001) in Figure 6B. In terms of network growth, the average shortest path length relative to the logarithm of the number of authors increases, indicating a gradual growth in the average path length between authors as they are added to the network (Figure 6C). However, on the other hand, the average size of large components (communities) had a slight decrease until 2010 and has been increasing steadily since then (Figure 6D).

If we want to find the biggest groups of authors who are all connected to each other through some path of co-authorship relationships, we may compute the largest connected components through social discovery or community detection algorithms. In other words, if we pick any two authors within these components, we should be able to trace a path of co-authorship relationships from one to the other, even if they have not directly collaborated on a paper. The size of the largest connected component can provide insights into the collaborative nature of the research field. A larger connected component might suggest a high degree of collaboration and interconnectedness among researchers in the field. Four largest connected components and their most influential authors is as Figure 7.

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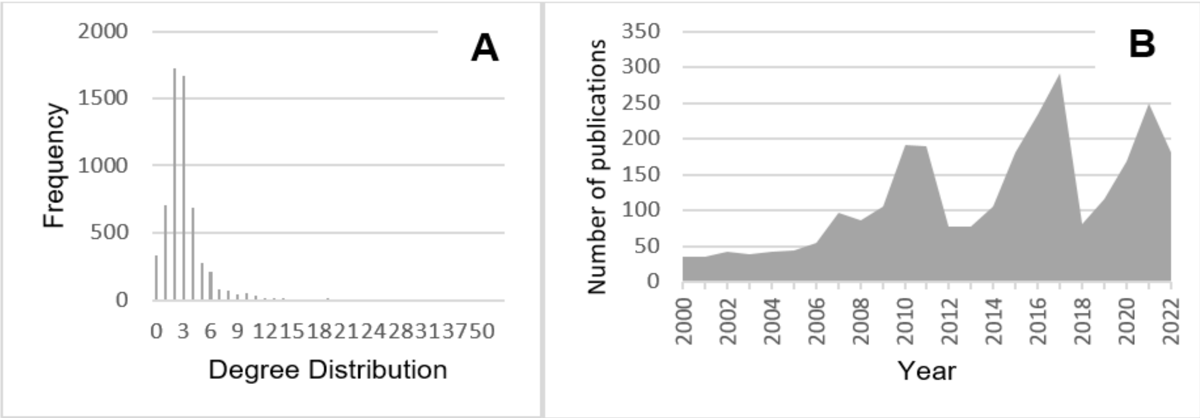

Figure 5. The initial statistics regarding the number of authors per article in the field of psychopathology (A) and the number of publications per year (B)

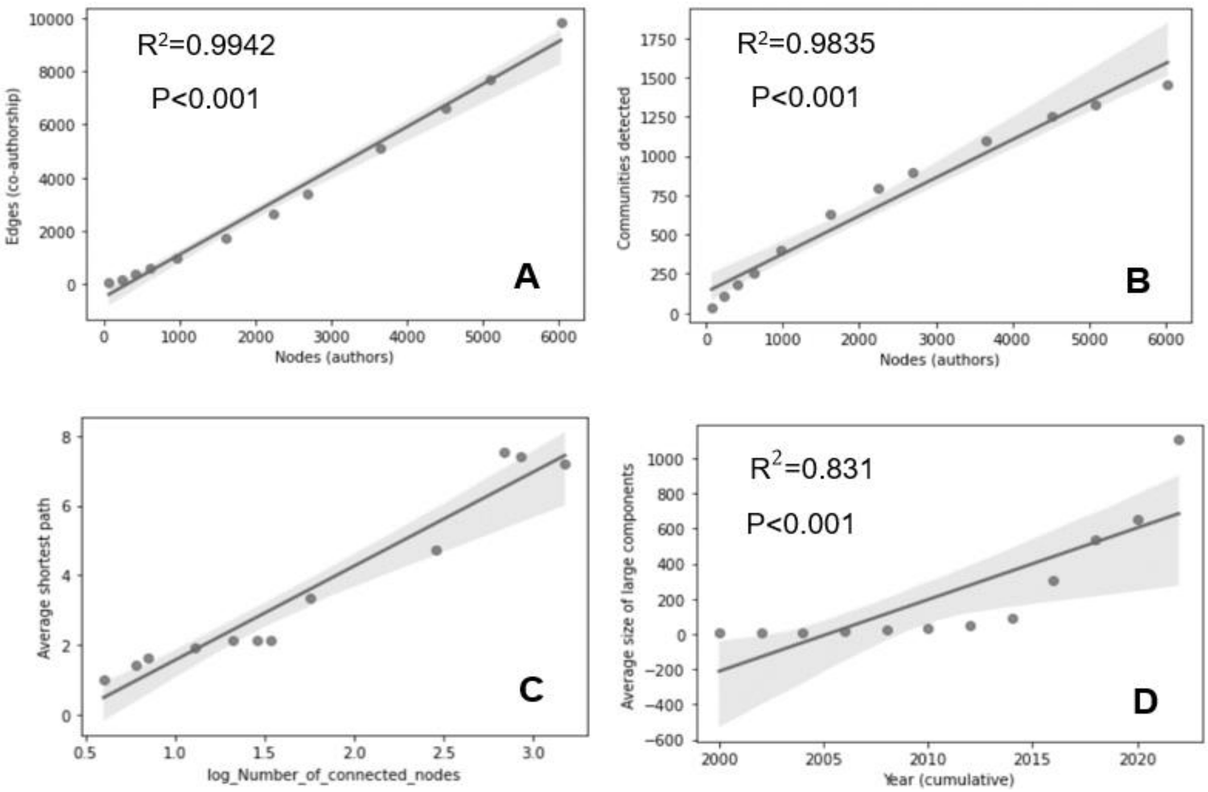

Figure 6. The relationship between the increase in the number of nodes and edges (A), the increase in the number of nodes with communities (B), the increase in the number of connected nodes with the average path length (C), and the increase in the size of large components of the network with time (D)

Finally, to describe the network and identify the most crucial nodes (authors), centrality measures can be applied to the network and the output reported. Table 3 shows the importance of authors from different centrality perspectives (degree, betweenness, and closeness). Of course, changing the node importance measure may result in changes in the ranking of top authors. We identified prominent authors based on three different centrality measures. As shown in Table 3, Eiko Fried had the highest collaboration in the co-authorship network based on degree centrality and appeared to be a key author who linked multiple communities. However, according to closeness centrality, Zijuan Ma had a high rank indicating a short communication path with other researchers. Important authors were identified based on four major components using network diagrams in Figure 7.

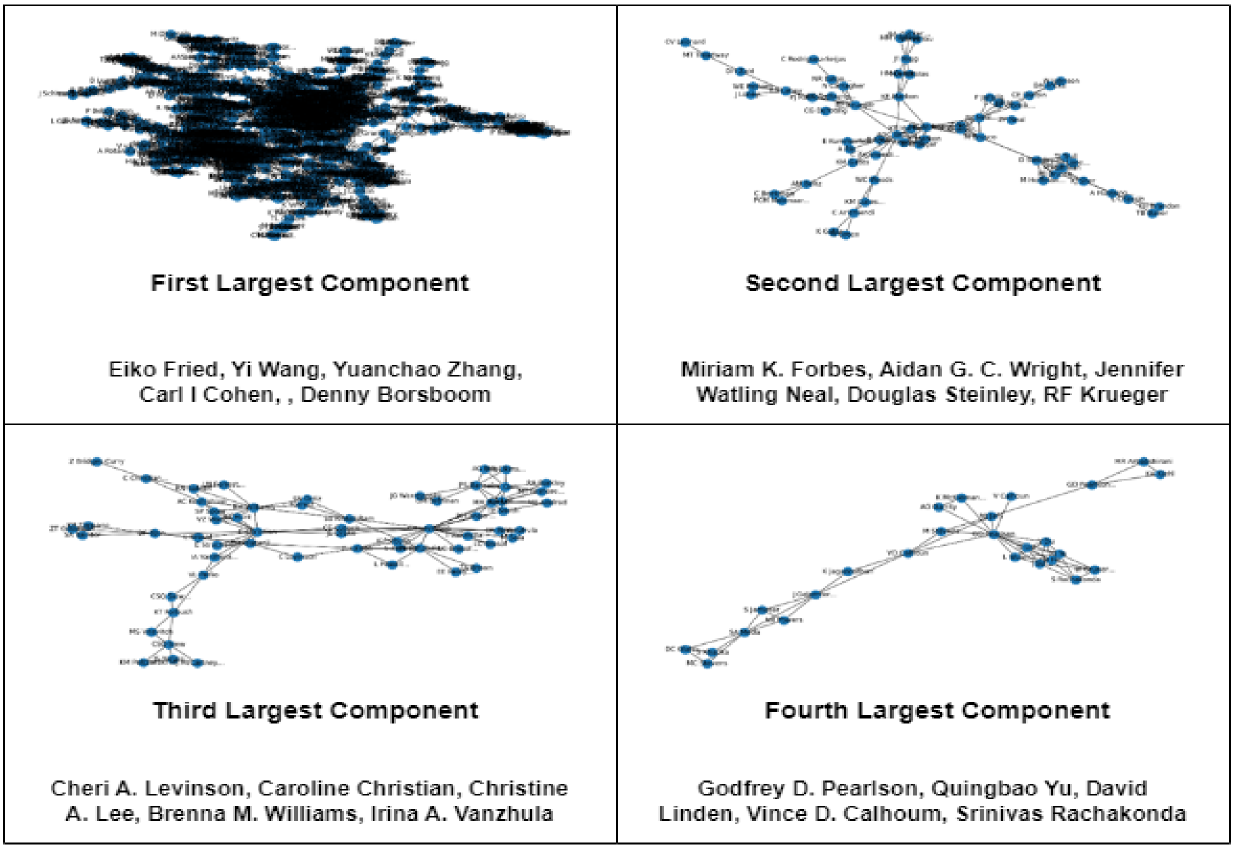

Figure 6. The discovery of automatic clustering has led to the formation of four communities, each with their top writers based on the number of connections. The ranking of top writers is from left to right

Table 3. Five top writers have been ranked based on three common centrality criteria along with a calculated score

	Degree centrality	
Central tendency	University	**Author**
0.01112	Leiden University, Netherlands	**Eiko Fried**
0.01062	Chinese Academy of Sciences , Beijing, China	**Yi Wang**
0.0083	Capital Medical University, China	**Jianguo Zhang**
0.00647	University of Electronic Science and Technology of China	**Yuanchao Zhang**
0.0063	SUNY Downstate Health Sciences University, USA	**Carl I Cohen**
	Betweeness Centrality	
Central tendency	University	**Author**
0.01627	Leiden University, Netherlands	**Eiko Fried**
0.01241	University of North Carolina at Chapel Hill, USA	**W Liu**
0.01137	National University of Singapore, Singapore	**Sacha Epskamp**
0.01125	South China Normal University, China	**Zijuan Ma**
0.01104	Chinese Academy of Sciences, Beijing, China	**Chen Chen**
	Closeness Centrality	
Central tendency	University	**Author**
0.05731	Nanjing University, China	**Zijuan Ma**
0.05576	Chinese Academy of Sciences, Beijing, China	**Chen Chen**
0.05461	Guangxi Medical University, China	**Jianrong Liu**
0.05426	Beijing Normal University, China	**Yanqiang Tao**
0.05405	Department of Communication, Renmin University of China, China	**Wenjun Liu**

In addition to our main analysis, we also conducted text mining on all abstracts to identify research topics. Topic modeling provides a low-dimensional interpretable representation of documents and has been used for tasks such as text analysis, document classification, and information retrieval (Churchill & Singh, 2022). Based on the utilization of network search for topic modeling, the maximum coherence score (0.43684) was achieved with a maximum of 9 topics. This means that there are 9 major categories of keywords in searching the psychopathological papers with network analysis approach. Table 4 displays the ratios of indicators for each topic. For instance, "Network, Analysis, Use, Study" are the most popular representative words of the articles in this field. Furthermore, Deeper analysis may provide more information about the relations between top authors and major topics. By determining the affiliation of each article to one of the 9 topics, more information is revealed. For example, among 38 articles authored by EI_Fried, if we consider five individuals with the highest co-authorship interactions, 36 cases (97%) belong to topic 5 and one case (2%) belongs to topic 1. All 17 journals authored by Yi Wang are affiliated with topic 5 and two collaborations with Jianguo Zhang are recorded among them. Among the 13 journals authored by Jianguo Zhang, 12 (92.3%) were related to topic 5 and 1 (7.7%) to topic 9. Yuanchao Zhang had 11 articles, of which 10 (90.9%) were related to topic 5 and 1 (9.1%) to topic 1. Finally, for Carl I Cohen, 16 articles were found, of which 15 (93.75%) were related to topic 5 and 1 (6.25%) were related to topic 1. Except for the collaboration between Yi Wang and Jianguo Zhang, no other collaboration was found among the top five authors.

The distribution of topics in all publications by the five main authors is shown in Figure 8b, while the distribution of articles across all topics in all journals is shown in Figure 8a. Considerably, topic 5 (User, Event, Family, Comment) is the most popular topics in action. This indicates that research topics that had a high ratio of tokens did not necessarily attract a significant number of authors with high centrality.

Table 4. Identification of distinctive words through topic modeling with LDA

Topic Number	Keywords	Ratio of indicators (%)
1	Network, Analysis, Use, Study	76.90%
2	Score, Negative, Positive, Severe	10%
3	Brain, Neural, Resting_state, Activity	8.70%
4	Gene, List, Stratified, Sex	1.10%
5	User, Event, Family, Comment	1.10%
6	Face, Mode, University, Drastic	0.80%
7	Team, Meeting, Coordinate, Seminar	0.60%
8	Face, Mode, University, Drastic	0.50%
9	Poverty, Distribution, Synergistic, metaphysical	0.40%

Figure 7. Comparison of the distribution of identified topics through LDA. Figure A shows the distribution of topics among all publications. Figure B displays the distribution of topics among the top five authors (based on centrality measure). Topic five had the highest share in both charts

In particular, an increasing number of scientific studies are being conducted on the application of machine learning in the field of Psychopathology research. While the importance of interdisciplinary collaboration in this area has been emphasized, there is little information available on the current state of existing networks. Undoubtedly, interdisciplinary research collaboration is necessary for conducting transformative research and accelerating innovation. Our analysis of bibliometric data revealed an increase in publications over the past two decades. The majority of research was published in specialized journals such as Schizophrenia Bulletin, American Journal of Psychiatry, PLOS One, Psychological Medicine, and Frontiers in Psychology, indicating that most articles in this field have been published in relevant specialty journals, with the exception of PLOS One which is more general and publishes articles on other topics as well.

The modeling pattern of increasing network communications, along with the growth trend of the number of authors, as indicated by similar studies (Viana et al., 2013), suggests an increase in the size of communities in the co-authorship network of computational researchers in psychopathology. It appears that there has been a two-way growth in the co-authorship network (both authors and works). Another important feature is that our network almost meets the definitions of a small-world network (Khouzani & Sulaimany, 2022). While the clustering coefficient has remained high throughout the research period, the average shortest path has grown proportionally with a gentle slope logarithmically with the number of nodes. The small world property implies that researchers within a particular field or scientific community are typically linked to each other through a relatively small number of co-authorship relationships. This phenomenon arises due to the collaborative nature of scientific research, where researchers frequently collaborate with their peers, forming a web of connections.

Furthermore, the examination of leading authors from the perspective of centrality criteria indicates that these individuals are often affiliated with scientific domains in psychology, while for advancing network analysis in fields related to Psychopathology, it is better for these scientists to have greater collaboration with computer and data science researchers. Therefore, the absence of computer science researchers in interdisciplinary research on Psychopathology is evident.

Conclusion

The use of computational methods such as machine learning can lead to richer findings and strengthen results in various fields. Network analysis methods, which have found extensive applications in psychopathology, are themselves considered computational applications in the field of psychology. Although network analysis-based psychopathology research has been reviewed by various scientific perspectives, it has not been viewed from a co-authorship network view, and such a perspective can provide a better understanding for future scientific communications in this field, especially since the results of co-authorship network findings can be further strengthened with the help of text processing techniques and network analysis, creating more knowledge, which was the main subject of this study.

In summary, this study revealed the structural characteristics of co-authorship networks through network analysis and their temporal changes. The research community has grown over the past two decades, and prominent authors have been identified based on centrality measures. These authors were mostly psychologists, although some authors from other scientific fields were also observed, indicating interdisciplinary nature of this field. Therefore, for those interested in initiating or expanding collaborative research in this area (both psychologists and computer specialists), one option is to establish connections with researchers who have high centrality. Another option for conducting future studies could be examining the categories of the 19 classifications that have not been investigated or have fewer publications. Table 5 highlights disorders that may have potential for more research in the field of network analysis, those with no related publications or paper count less than ten.

Table 5. Categories in the classification of psychological disorders that constitute zero or a small proportion of the total number of network analysis related papers

Category	Number of articles (out of 783)
Paraphilic Disorders	0
Elimination disorders	0
Substance-related and addictive disorders	3
Neurocognitive disorders	7
Disruptive, impulse-control, and conduct disorders	7
Somatic symptom and related disorders	7
Dissociative disorders	7
Neurodevelopmental disorders	9

What was previously known about the topic of computational analysis of psychopathology was that it is an interdisciplinary field that is rapidly developing. However, what we have achieved in this study is the first assessment of the structure and characteristics of scientific collaboration in the field of computational psychology, including analysis of co-authorship networks and understanding current trends in research collaboration, the number of communities, prominent authors, and their career backgrounds. This study provides scientific evidence to help plan a new collaboration strategy that can enhance the applications of machine learning for psychological research.

One potential future development of this research could be the creation of weighted networks for better modeling of the connections between authors. Previous calculations have only considered the existence of a connection between two authors in the case of co-authorship. However, if factors such as the number of joint publications or an author's position in an article and their contribution to its creation were taken into account, a more accurate network could be constructed with more information and weighted connections. In this scenario, calculating the co-authorship network analysis parameters would may result in the more accurate findings.

In this study, we used the LDA method (Tong & Zhang, 2016) for topic modeling and found that the optimal temporal coherence was achieved with nine topics. We observed that topics with high token ratios were not necessarily popular research centers among authors with high centrality. For example, articles related to topic 5, table 4, were more prevalent among central authors than those related to other topics. Furthermore, a recent study showed that LDA can be used for predicting links in co-authorship networks. Therefore, identifying topics may provide more information about future collaboration opportunities (Chuan et al., 2018).

One limitation of this research, related to the nature of co-authorship analysis, is that co-authorship only indicates a potential for collaboration and does not necessarily imply actual scientific collaboration (E Fonseca et al., 2016). Additionally, the specific contribution of each author to the publication cannot be evaluated through this method. In fact, it has been reported that as the number of authors increases, the level of author participation decreases and it is not possible to estimate contributions from author rankings (Corrêa et al., 2017). Therefore, the use of centrality degree as a measure of scientific productivity should be avoided.

Disclosure Statement

Author declare that they have no conflicts of interest.

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