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Connecting for Well-being: A Role-Based Network Analysis of Online Mental Health Communities

Abstract

This paper attempts to fill two gaps: (i) offers a method to empirically identify and classify user roles based on patterns of topic engagement within online mental health groups, and (ii) reveals the influence of these roles on information dissemination in these virtual environments.

We analysed 8,580 posts out of 90,626 from the r/MentalHealth subreddit. Our approach identified 12 main discussion topics: suicidal behaviour, mental well-being, emotional experience, interpersonal connections, education, sleeping, video gaming, professional life, depression and anxiety, cognitive recall, parenting, and panic attacks. Employing network theory, we obtained a topic-user network, including 8,962 relationships, based on the topics discussed. After a network projection process, we detected four subgroups in a user-user network of 7,564 users and 12,717,205 relationships. We classified user roles as life jugglers, mindful wellness seekers, resilient individuals, and emotional connectors. We investigated these users' structural positions ("centralities") to assess their influence on information flow in the network. While wellness seekers, resilient individuals, and emotional connectors demonstrated that they played a vital role in disseminating their knowledge and experiences within the network, life jugglers did not exhibit any responsibility in information dissemination.

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Keywords: online mental health communities, mental health, user roles, network analysis, structural role theory, information dissemination

Word count: 10,358

1. Introduction

Mental health is a state of well-being where individuals can manage life's challenges, realise their abilities, learn effectively, perform well at work, and make meaningful contributions to their communities (World Health Organization, 2022). A range of global challenges—economic downturns, social unrest, public health emergencies, large-scale humanitarian crises, forced migration, the escalating climate crisis, and the COVID-19 pandemic—have severely impacted mental health. These factors have led to an increase in mental health disorders worldwide, many of which continue to go untreated. Mental illness encompasses any disorder that affects emotions, behaviours, or cognitive processes (Chakravorti et al., 2018). In 2019, around 970 million people globally were affected by mental disorders, with anxiety and depression being the most common (World Health Organization, 2022). In the U.S., 21% of adults, or over 50 million people, have experienced a mental illness, with 4.8% having severe suicidal thoughts—about 12.1 million adults (Reinert et al., 2022). Additionally, 16% of youth reported at least one major depressive episode in the past year, and over 2.7 million experienced severe depression.

People have shifted away from conventional communication methods, opting for online interactions and utilising digital platforms to embrace a novel communication paradigm (Dao et

al., 2017). These digital communication platforms have also revolutionised how individuals seek support and information on mental health concerns by connecting them with others struggling with mental health problems. Online health communities are one of these platforms. They were built as forums for individuals by providing an inexpensive and convenient virtual space to connect, share experiences, and discuss various aspects of mental well-being without any geographical limitation (Bauer et al., 2013; De Choudhury & De, 2014). Also, because of the privacy and anonymity on these platforms, individuals might be willing to write about even taboo subjects and emotions.

Existing research on online health communities has approached the analysis of these platforms from diverse angles. Some studies have conducted content analysis on user-generated posts within online mental health communities, employing topic modelling to identify recurring themes or topics and sentiment analysis to measure the emotional tone of the discussions (Alambo et al., 2020; De Choudhury & De, 2014; H. Wang et al., 2022). Others have focused on examining the structural properties of networks at the content level, such as network topology and network of frequently used keywords (Bi et al., 2020; Surian et al., 2016). Additionally, there has been research at the user level, where content preferences and/or network properties are employed to characterise users and identify distinct roles within these communities (Buntain & Golbeck, 2014; Grayson & Greene, 2019; M.-L. Li et al., 2023).

On the other hand, little focus has been placed on understanding the dynamics of user roles based on their structural positions ("centralities") in online mental health communities. This understanding is vital for fostering a more supportive and inclusive environment. Community leaders and moderators can tailor their interventions to enhance these users' influence by identifying the distinct user roles that occupy central positions in the network. These roles are pivotal in disseminating information and providing support and empowering

them can lead to a more efficient flow of knowledge and emotional care throughout the community. Simultaneously, understanding the needs of less central roles allows for designing more targeted interventions to better engage and integrate these users into the community. This role-specific approach ensures no user group is left behind, creating a more inclusive and supportive environment for all members. In this regard, we seek an answer to *how different user roles in online mental health communities influence the flow of mental health support and information.*

To answer this question, our approach primarily focused on how individuals interact within the community by discussing various topics instead of solely analysing user interactions such as commenting or replying to one another's posts. This content-driven approach is critical in online mental health communities, where the nature of the discussions often reflects users' mental health needs and challenges. This alternative angle allowed us to uncover the relationship between content engagement and users' structural positions in the network, offering novel insights into how different user roles impact the dynamics of information dissemination.

Therefore, we collected and analysed discussions from the r/MentalHealth subreddit. We analysed topics being discussed, identified users' structural positions in the network of discussions, classified the user roles based on what they discussed, and investigated these roles' influence in the community. This research offers an opportunity to develop targeted interventions for moderators and administrators by uncovering diverse roles.

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2. Theoretical Background

Applying the network lens, as discussed by Borgatti and Ofem (2010), enables the analysis of various social systems. Networks involve connections or relationships in multiple forms, such as social relations (e.g., kinship), similarities (e.g., same gender, same club), mentalities (e.g., likes, hates), interactions (e.g., helped, harmed), and flows (e.g., information, influence).

Network theory delves into actors' characteristics and how their relationships influence and limit their decisions and behaviours. Social network analysis (SNA) is the predominant method for studying the attributes and relationships within various entities. Feicheng and Yating (2014, p. 232) describe SNA as a "quantitative method developed by sociologists, based on mathematical models and graph theory." This approach is not merely a way of looking at relationships but is fundamental to understanding network concepts, as Borgatti and Ofem (2010) emphasised. SNA enables the detailed examination and illustration of social structures and behavioural models across individuals and populations, drawing on contributions from researchers (Borgatti et al., 2009; Krause et al., 2007; Lewis et al., 2008; Takhteyev et al., 2012). At the heart of SNA is the network itself, composed of actors—individuals, teams, and departments to organisations, industries, and beyond—each capable of forming relationships with another entity.

On the other hand, structural role theory provides a lens for understanding how an individual's position within a network shape their behaviour and influence (Biddle, 1986). According to structural role theory, individuals occupy specific roles within a social structure based on their position in the network. These roles are not arbitrary; they come with defined expectations, behaviours, and levels of influence determined by an individual's relational

position relative to others. In this sense, roles are structured and shaped by individuals' interactions and relationships within their communities. Users in online health communities are not just passive participants; their roles within the network influence how they engage with others, provide or receive support, and contribute to the dissemination of information.

Community detection, a pivotal concept in SNA, is crucial in identifying clusters or subgroups within a network. These subgroups, comprising actors more densely connected with each other than the rest of the network, are the building blocks of social groups. Understanding these groups is key to comprehending how social groups form and how interactions within these groups shape individual behaviours and roles. In structural theory, community detection unveils an individual's broader structural position. It allows us to identify meaningful personas by linking structural positions identified by community detection with the thematic content users engaged with.

While community detection unveils structural positions, the centrality measures refine our understanding. These measures, when applied, evaluate the significance of roles within the network, providing a deeper insight into the network's dynamics. For instance, degree centrality, which measures an individual's number of connections to others in the network, is a powerful tool in this regard. A high degree centrality indicates direct connections to many others, implying a significant influence (E. Y. Li et al., 2013). This means they have more influence and can quickly spread information to a larger audience. For example, if someone in a social network knows many people, they can easily share ideas or information with others. However, others are also more likely to influence them because of their numerous connections.

Closeness centrality measures how close an individual is to all other people in the network (Catanese et al., 2012). If someone has high closeness centrality, they can quickly reach anyone else in the network with fewer steps or connections, making them efficient at spreading

information or ideas. Imagine someone who can easily communicate with everyone in a group because they are well-connected to others, allowing them to spread news quickly.

Eigenvector centrality takes into account not just the number of an individual's connections but also how important their connections are (Abbasi et al., 2011). If someone is connected to other highly influential people, their influence increases. Think of it as being influential by association—connecting to important people makes you more important, too. This type of centrality measures how well-connected and influential an individual is within the entire network.

Betweenness centrality measures how often an individual acts as a bridge between different groups of people (Wasserman & Faust, 1994). If someone has high betweenness centrality, they connect otherwise separated groups, allowing them to control the flow of information between those groups (Baek & Kim, 2015; Freeman, 1978). They play an important role in keeping the network connected. For example, they might be the only link between two groups, meaning they control how information passes between them.

3. Online Mental Health Communities

Rheingold (1993) defined online communities as bringing together individuals with mutual interests, often forming close-knit relationships in virtual spaces. Studies on Reddit have shown that these communities serve as platforms for discussing mental health, where users exchange information, share struggles, and seek support (De Choudhury & De, 2014). Anonymity in these spaces often encourages more intimate conversations, particularly around mental health challenges.

Research has highlighted how individuals express themselves across different mental health-related subreddits. For instance, users in bipolar and depression communities share

experiences related to sleep disorders and financial problems, with depression forums displaying a wide range of emotional tones and narrative genres (Yoo et al., 2019; Sik et al., 2021). Similarly, distinct concerns and discussion patterns emerge across subreddits for depression, post-traumatic stress disorder, anxiety, and bipolar disorder (A. M. Park et al., 2018; J. Y. E. Park et al., 2020). For example, users in the bipolar disorder community showed more interest in medication, whereas users in the depressive disorder community were more interested in suicide issues. Individuals with depression, post-traumatic stress disorder, and anxiety shared overlapping concerns, such as sleep and work-related problems.

The linguistic characteristics of mental health discourse also vary significantly. Language in mental health forums is more damaging compared to neutral contexts, with anxious and depressed users displaying distinct psychometric traits (Iavarone & Monreale, 2021; Ireland & Iserman, 2018). Notable differences in sentiment are evident across mental health subreddits, with communities like the anxiety subreddit exhibiting more negativity while others, like the autism subreddit, use more positive emotions (Kim et al., 2023). Additionally, posts in the mental health subreddit had a higher word count on average, while the schizophrenia subreddit exhibited shorter, more concise posts.

The COVID-19 pandemic heightened mental health discussions on Reddit, particularly in subreddits like r/HealthAnxiety and r/COVID19_support, with concerns shifting from virus fears to uncertainty about new variants (Leung & Khalvati, 2022; Low et al., 2020). Alambo et al. (2020) found that support groups focused on attention deficit, hyperactivity disorder, eating disorder, and anxiety exhibited the most negative semantic changes during this period. There was a notable topical correlation (co-occurrence of content) between depression and COVID-19-related posts in September 2020, and similarly, a strong correlation between substance use disorder and pandemic discussions in August 2020. Additionally, students' mental health

struggles were exacerbated by remote learning, though social support on Reddit helped mitigate some challenges (Garcia et al., 2022).

While Reddit is a popular platform for mental health discussions, other communities such as BlueBoard and LiveJournal also provide valuable insights into user interactions, emphasising topics like depression, anxiety, and social isolation (Carron-Arthur et al., 2016; Nguyen et al., 2017). Across these platforms, users offer experiential knowledge and emotional support, while sentiment-bearing differences provide opportunities for targeted interventions (Dao et al., 2017). Moreover, misinformation in online health groups remains a concern, as inaccurate medical information can spread widely in these communities (Bizzotto et al., 2023).

Some studies have utilized topic preferences and user behaviour to identify roles in online communities. Liu et al. (2019) proposed a method integrating user behaviour and content to classify roles in social networks on Weibo. Choi et al. (2015) explored characteristics of threaded conversations on Reddit, identifying roles like initiators and commentators. Kou et al. (2018) analysed social roles in an online UX community, revealing roles such as knowledge brokers and conversation facilitators. Z. Wang and Zhang (2016) identified collaborative roles like starter and follower on Zhihu.com, a health-focused platform in China. Yang et al. (2019) examined role dynamics, identifying roles like welcomers and story sharers in the American Cancer Society's Cancer Survivor Network. These studies emphasize how role identification enhances understanding of user dynamics in online communities.

Table 1 provides a comprehensive overview of previous studies, highlighting their distinct methodologies, approaches, data collection platforms, periods, and sample sizes after data preprocessing. Recognising online communities as networks highlights the interconnectivity within digital interactions, making Social Network Analysis (SNA) a fundamental approach. For example, at the content level, Surian et al. (2016) and Hung et al. (2020) analysed Twitter

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discussions on HPV vaccines and COVID-19, forming follower networks to examine topic clustering within communities. Pirri et al. (2020) studied Twitter posts during World Lupus Day at the user level, identifying top influencers through retweet networks. Bi et al. (2020) examined albinism in a Chinese health community, analysing community evolution and network topology. Weng and Lin (2022) studied bot behaviour during the COVID-19 pandemic using retweet networks, focusing on network centralities and bot detection. M.-L. Li et al. (2023) developed a model tracking role evolution in a design community, identifying roles like passive members and novice designers. Grayson and Greene (2019) used graph embedding to explore how user roles, such as “loyal” and “vagrant,” shift over time. Buntain and Golbeck (2014) analysed Reddit user behaviour, identifying roles like the "answer-person." However, research specifically using network features to identify roles in online health communities remains limited.

Insert Table 1 about here

4. Methodology

We selected the r/MentalHealth subreddit, a central forum for discussing, sharing, and seeking support on mental health illness and wellness on Reddit. Reddit is a social media platform composed of numerous user-created communities known as “subreddits,” each dedicated to specific topics or interests. These subreddits, denoted as /r/subreddit_name (e.g., /r/gaming for gaming discussions), function as individual forums where users can post content and engage in discussions related to the subreddit’s focus (Dictionary.com, n.d.). Users can subscribe to subreddits that align with their interests, customizing their Reddit experience to

display content from those communities on their personalized feeds. This structure allows Reddit to host a vast array of discussions, ranging from broad subjects like news and entertainment to niche topics and hobbies. Although the demographics of this subreddit are unknown, generally, Reddit users are mostly American (49.9%), male (67%), and young, with 22% being 18-19 years old and 14% being 30-49 years old (Low et al., 2020).

First, we retrieved the content ID, date, author, title, text, and type of 90,626 posts during the first quarter of 2023 through Communalytic (Gruzd & Mai, 2022). Communalytic is an easy-to-use social media data collector designed to collect publicly available data from Reddit, Telegram, YouTube, X (known as Twitter), Bluesky, and Mastodon.

The content ID is a univocal identifier associated with the content. The date involves the date and time of content posted to the website. The author is the username of the author of the content. While the title includes the content's title, the text involves the content itself. Redditors can comment on posts and respond in a conversation tree of comments. So, the type can be either submission/post, comment, or reply.

In the second step, we undertook data cleaning and preprocessing. Initially, we focused on extracting only submissions or posts that were conversation starters. This was because submissions typically initiate discussions, making them crucial for understanding the broader themes and topics discussed within the community. Out of the total 90,626 posts, we identified 22,769 as submissions. The remaining posts, which included comments or replies, were excluded at this stage since they primarily functioned as responses to ongoing discussions rather than initiating new conversations. By narrowing down the dataset to submissions, we ensured that our analysis focused on the primary content driving discussions within the subreddit.

Then, iteratively, we applied an extensive qualitative analysis and automated data preprocessing using WordStat 8.0. We eliminated duplicate posts. We removed system-

generated posts because they do not contribute meaningful user-driven content to the discussions. We excluded non-English content, as Reddit's primary language is English, to ensure consistency in the language of analysis and avoid potential misinterpretations or biases in understanding the discussions.

Additionally, we removed posts that had been deleted or removed. The content of a post might be deleted or removed by the user, moderators, or Reddit's automated systems. In such cases, posts involve tags of "[deleted]" or "[removed]." We removed posts with no authors because authors were required to create a topic-user network. We deleted posts generated by bots as they do not reflect authentic user engagement and could skew the analysis. We removed posts asking for participants to join research studies or complete surveys as these posts are not related to the actual content discussions within the community and would not contribute meaningfully to our examination of mental health conversations.

Then, we applied the following data cleaning and processing steps to prepare the submissions for topic modelling analysis. We concatenated the title and text of each post because users often start a post with the title and finish below the text body (Chakravorti et al., 2018). We removed numbers, punctuation, extra white spaces, non-alphabetical characters, non-word emoticons, system-generated words or characters, and hyperlinks. We corrected misspellings and replaced words spelt informally with formal spelling, for example, "ive" to "I have" and "ppl" to "people" (Leung & Khalvati, 2022). We excluded common stop words such as "the," "a," and "and." We lemmatised words to analyse the inflected forms of a word as a group together (Ding et al., 2021). For example, we treated cars, car's, and cars' as car. We converted all the words to lowercase. We removed words appearing less than five times across posts to reduce noisy words. Also, we deleted posts that were less than 50 words because short posts might produce undesirable outcomes (Ding et al., 2021). The final sample included 8,580 posts.

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We extracted topics by using WordStat 8.0. The software computed a word-by-document frequency matrix and performed a non-negative matrix factorisation (NNMF). All words loading higher than a specific criterion were retrieved as part of the extracted topic. The NNMF method is faster and can handle larger matrices. However, no standardised procedure exists to determine the optimal number of topics (Németh et al., 2021). Therefore, we combined quantitative and qualitative approaches for this task. We ran topic models with varying numbers of topics, from five to twenty. We tried to get topics that were not too broad but still not over-clustered. After topic extraction, we determined labels for each topic using the top keywords and qualitative judgments.

Then, we used QDA Miner 8.0 to code each post automatically into identified topics. A post could belong to more than one topic. As a result, we extracted a matrix that included the post ID, author name, and corresponding topic distribution. We used this extracted matrix to create a user-topic network. We created a bipartite or two-mode network, including topics and users. If a user wrote something about a specific topic, we created a relationship between this user and that specific topic. A user could write about the same topic more than once. For this reason, we calculated a relationship weight by counting the edges between the same user and the same topic. This weight showed the strength of the relationship (Haythornthwaite, 1996). We obtained a two-mode and weighted network including 8,962 relationships. After that, we transformed the two-mode network into a one-mode network by projection (Borgatti et al., 2009). We used the R iGraph package to project and analyse the network. We selected users as the primary actors to study user-level interactions. If two authors wrote about the same topic, a relationship occurred between them. Furthermore, two members could write about the same topics more than once, so this function also calculated relationship weights. Finally, we obtained a weighted and one-mode network including 7,564 users and 12,717,205 relationships. To detect

their structural positions in the network, we identified edge betweenness, fast-greedy, multilevel, Walktrap, label propagation, spin-glass, leading eigenvector, and Infomap as proper community detection algorithms. The spin-glass algorithm was central processing unit intensive (Omran & van Etten, 2007). This problem limited its use on large networks, and it performed worse when the network size increased. As a result, we excluded the spin-glass algorithm. In addition, we excluded the edge betweenness algorithm due to its slow speed (Newman, 2004). We reviewed the modularity yielded by each algorithm. Modularity is a quality metric to evaluate how good a particular network division is in communities (Mislove, 2009). We selected the algorithm yielding the highest modularity, identified users' structural positions, and calculated users' network centralities.

Then, we analysed users' detected structural positions and the topics they discussed in the network to identify user roles. As the last step, we aggregated the degree, closeness, eigenvector, and betweenness centralities at the user role level by taking the average to analyse each role's influence on information flow in the online health community.

5. Results

Figure 1 summarises how the structural role theory is methodologically operationalised, including the inputs and outputs used to identify and classify the roles empirically. Topic modelling yielded twelve topics: suicidal behaviour, mental well-being, emotional experience, interpersonal connections, education, sleeping, video gaming, professional life, depression and anxiety, cognitive recall, parenting, and panic attacks. Table 2 summarises explanations and high-probability terms belonging to these particular topics.

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Insert Figure 1 about here

Insert Table 2 about here

To better understand each topic's meaning, we investigated its most representative Reddit posts. Table 3 shows the topics and their associated Reddit posts.

Insert Table 3 about here

We detected communities after using topic discovery results to develop a network. Table 4 summarises the community detection algorithms and results. According to this table, while the fast greedy, multilevel, and leading eigenvector algorithms detected four communities, the Walktrap algorithm yielded five communities. On the other hand, the label propagation and Infomap algorithms could not detect any communities. The multilevel algorithm yielded the highest modularity, with 0.2123, so we selected the community distribution based on that algorithm. According to Figure 1, the community detection yielded four subcommunities.

Insert Table 4 about here

Table 5 includes the topic distribution across each community. The first community involved 2,002 users. They mainly discussed parenting, interpersonal connections, suicidal behaviour, professional life, and education. We labelled this community as *life jugglers*, navigating multiple life challenges simultaneously. The second community consisted of 2,011 users. They mostly talked about mental well-being in general. We described this community as *mindful wellness seekers*, sharing resources, experiences, and strategies to foster positive mental well-being, promote self-care practices, and prioritise their mental well-being. The third

community included 1,614 users. They mainly talked about depression, anxiety, and panic attacks. We identified these users as *resilient individuals*, who faced specific mental health challenges related to depression and panic attacks. The last community includes 1,937 users. They were mainly interested in the topic of emotional experience. We characterised these users as *emotional connectors*, centred around intense emotional connections.

Additionally, Table 5 shows network centralities. The results showed mindful wellness seekers had the highest degree of betweenness centralities. Emotional connectors had the highest closeness centrality, and resilient individuals had the highest eigenvector centrality. On the other hand, life jugglers had the lowest centrality metrics.

Insert Table 5 about here

6. Discussion

Proficient psychiatrists can distinguish mental disorders or problems from clinical pathology and experiences (Yoo et al., 2019). However, it might be essential to investigate whether individuals share experiences, concerns, problems, or medical information in online communities, as mental health problems or disorders are often considered challenging to disclose due to privacy issues. Thus, people seek help or information through online communities. These

online platforms can connect people to information, resources, and other individuals, creating opportunities for support and education (Burns et al., 2007). A detailed understanding of peoples' perspectives might remain crucial in online communities.

This research extends existing frameworks for categorising user roles within online health communities. While prior studies, such as those by Althuniyan (2023), Wang and Zhang (2016), and Yang et al. (2019), have primarily focused on general behavioural functions or social support categories, this study offers a more detailed classification of users personas grounded in network analysis. Including network centrality measures (e.g., degree centrality, betweenness centrality, eigenvector centrality, and closeness centrality) enables a deeper exploration of how users' positions within the community influence their roles and interactions. This theoretical approach complements prior research and bridges the gap between behavioural roles and structural dynamics, enriching the understanding of user engagement in digital mental health ecosystems.

This study underscores the interplay between users' experiences, motivations, and network positions. The research highlights the diversity of user needs and preferences in online mental health communities by identifying personas such as mindful wellness seekers, resilient individuals, emotional connectors, and life jugglers. This perspective advances theory by emphasising the fluid and context-dependent nature of user roles, moving beyond static categorisations to account for the dynamic interplay between users' behavioural patterns and the structural characteristics of the community.

For example, *mindful wellness seekers* demonstrated the highest degree centrality and betweenness centrality, indicating their extensive connections and vital bridging role between subgroups in the community (Akar & Dalgic, 2018). This result suggests *mindful wellness seekers* possess a central position that enables them to receive critical information, knowledge,

and resources. Their high betweenness centrality highlights their influence in facilitating the flow of information and mental support across different community segments. They can share their knowledge, experiences, and resources with a broad audience. *Resilient individuals* demonstrated the highest eigenvector centrality, indicating they are connected to other members with high centrality. Their elevated eigenvector centrality suggests that they have the potential to shape community discussions, offer valuable insights, and exert influence over others. *Emotional connectors* exhibited the highest closeness centrality, signifying their proximity to all other community users. Their strong relational ties make them natural facilitators of emotional exchange and support. On the other hand, *life jugglers* had the lowest centrality metrics across all measures. This indicates that they have fewer connections and play a less prominent role in bridging different subgroups within the community. The lower centrality of *life jugglers* may be attributed to the challenges they face in managing multiple responsibilities and priorities.

The research provides a theoretical foundation for designing role-specific interventions by linking these roles to their network centrality metrics. Platform moderators like Reddit use tools and community engagement to identify these user roles. For example, they can analyse user activity patterns, such as the frequency and type of posts, comments, and interactions, alongside network analysis metrics like centrality measures. Automated tools, such as sentiment analysis or machine learning models, may also assist in identifying user roles based on the content and tone of their contributions. Surveys or self-reported profiles could further complement these efforts, providing additional insights into user preferences and concerns.

For instance, *mindful wellness seekers*, akin to the informational support seekers identified by Althuniyan (2023), emphasise mental well-being and mindfulness practices. Moderators can identify these users through their active participation in self-care, meditation, and stress management discussions. Prevention efforts can include hosting regular mindfulness-

themed events, such as guided meditation sessions or journaling workshops, shared as pinned posts or live sessions (Sucich et al., 2022). Reliable information on mental health topics can be provided through curated resources, empowering individuals in their self-care journey (van Rijt et al., 2021).

Resilient individuals who primarily engage in discussions about depression, anxiety, and panic attacks can often be identified by their active participation in emotionally supportive and solution-oriented posts. Community leaders or moderators could use advanced analytics to highlight users with high eigenvector centrality, indicating their connections to other influential members. Once identified, these users can be offered opportunities to contribute through peer mentoring programs, knowledge-sharing platforms, or leadership development workshops. For example, cognitive-behavioural therapy is widely recognised for its effectiveness in treating anxiety, depression, and related disorders, focusing on modifying dysfunctional thought patterns and behaviours (Bhattacharya et al., 2023). These interventions can transform resilient individuals into mentors or role models, empowering them to guide and support others in their mental health journeys.

Emotional connectors, identified by their consistent engagement in personal and empathetic dialogues, exhibit high closeness centrality, highlighting their ability to connect with diverse users across the community. Rather than explicitly targeting individuals for art therapy, moderators can facilitate creative self-expression by creating and promoting spaces where all users can participate in art therapy, storytelling, or other creative outlets (Berger, 2014; Liao & Wang, 2021). These could include themed threads, competitions, or virtual workshops where users voluntarily share their creations, fostering an inclusive environment and encouraging emotional catharsis and connection.

Life jugglers, who balance multiple responsibilities such as parenting, professional life, and personal relationships, often have the lowest centrality metrics, indicating less community engagement. Moderators can design targeted programs such as online parenting workshops, forums for peer advice, or informational webinars tailored to the group's challenges. By creating accessible resources and flexible support options, such as recorded sessions or asynchronous discussions, moderators can help life jugglers manage their responsibilities while staying engaged with the community (Collins et al., 2020).

Moderators play a central role in designing and implementing these programs. Moderators often collaborate with mental health professionals, community volunteers, and advocacy groups on Reddit and similar platforms to curate and implement interventions. For example, they can use pinned posts, automated bots, and moderation tools to share resources, organise events, and monitor community dynamics. Platforms could further support moderators by providing training in mental health awareness and access to analytics tools that enable them to better understand user behaviours and roles. By facilitating such initiatives, moderators ensure that interventions are effectively integrated into the community and accessible to all user groups.

7. Conclusion

This study investigated how different user roles influence the flow of information and mental support in online mental health groups. At the theoretical level, results sustain essential conclusions. This study introduced an innovative approach to applying structural role theory within online mental health groups. It successfully offered a methodology for empirically identifying and classifying user roles based on engagement patterns across various topics. By meticulously analysing user interactions and engagement behaviours within these virtual communities, the research delineates individuals' distinct roles, ranging from life jugglers,

mindful wellness seekers, resilient individuals, and emotional connectors. The findings demonstrate that these differentiated roles pointedly impact the dynamics of information dissemination within these groups. Specifically, the study highlights how specific user roles act as pivotal nodes in the network, facilitating the flow of valuable information and resources, thus enhancing the group's overall effectiveness in supporting mental health. This contribution enriches the theoretical framework of structural role theory by adapting it to a novel context. It offers practical insights into optimising information dissemination strategies in online mental health platforms.

While this study provides valuable insights, it is essential to acknowledge some limitations that may affect the generalizability and interpretation of the findings. The study focused solely on the r/MentalHealth subreddit, which may limit the generalizability of the findings to other online mental health communities or platforms. Different platforms may have distinct user demographics, norms, and engagement patterns, which could influence the topics discussed and the identified user roles. The data used for analysis were limited to posts within the r/MentalHealth subreddit during a specific period. Also, deleted and/or removed posts that could not be retrieved from the Reddit platform were eliminated. Consequently, the study may not capture the full spectrum of mental health discussions and experiences across different time frames or other relevant platforms. The accuracy of topic modelling techniques can vary depending on various factors, including the choice of parameters, preprocessing methods, and data quality. While efforts were made to optimise the model's performance, there might still be instances of misclassification or inaccuracies in topic assignments.

Future studies might perform longitudinal studies to investigate the evolution of community dynamics, user roles, and topic trends over time. Tracking changes within the network structure and examining shifts in user roles and interactions can uncover patterns,

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resilience, and adaptations within the online mental health community. This longitudinal perspective can offer valuable insights into community engagement and support provision dynamics. They might extend the analysis to compare and contrast online mental health communities beyond the r/MentalHealth subreddit. They might explore online forums, social media groups, or specific mental health-focused platforms. This comparative approach can reveal variations in community structures, topics of discussion, and user roles across different platforms, providing a more comprehensive understanding of the online mental health landscape. Lastly, researchers might conduct rigorous evaluations to assess the effectiveness and impact of interventions targeting specific user roles within the online mental health community. They can implement interventions tailored to the identified user roles and evaluate their user engagement, support provision, and mental health outcomes. This evidence-based approach can contribute to developing effective interventions that enhance well-being and promote positive community experiences.

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Table 1. Summary of Previous Studies

Study	Method/Approach	Platform	Sample After Preprocessing	Period
Alambo et al. (2020)	• LDA • Transformer-based bidirectional language modelling	Subreddits: • r/depression • r/anxiety • r/SuicideWatch • r/Coronavirus • r/opiates • r/OpiatesRecovery • r/addiction	• 76,427 posts	• Between January 2020 and October 2020
Bauer et al. (2013)	• Qualitative categorization • chi-squared test	• Two diagnosis-specific German language forums	• 2,262 posts	• Between January 2006 and December 2016
Bi et al. (2020)	• Term frequency–inverse document frequency • LDA • Naive Bayes • Social network analysis • Sentiment polarity	• Baidu Tieba	• 5,110 posts • 35,424 comments • 3,188 users	• Between January 1, 2012, and March 14, 2019
Bizzotto et al. (2023)	• Content analysis	• Facebook groups	• 1,534 statements • 1,037 members	• Between January 2019 and December 2021
Buntain & Golbeck (2014)	• Social network analysis	• Several question and answer-based subreddits	• A network including 279 unique users	• July 2013
Carron-Arthur et al. (2016)	• LDA • Qualitative and domain knowledge processing	• Blueboard	• 131,004 posts	• Between October 1, 2008, and May 23, 2014
Chakravorti et al. (2018)	• Word2Vec • Skip-gram model • k-means clustering	Subreddits: • r/depression • r/SuicideWatch • r/anxiety	• 780,149 posts	• Between 2012 and 2018
Choi et al. (2015)	• Social network analysis • Semantic analysis • Gini coefficients	• Top 100 subreddits	• 695,857 posts • 18,093,422 comments	• Between March 13, 2014, and April 18, 2014

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Study	Method/Approach	Platform	Sample After Preprocessing	Period
			• 1,455,293 users	
Dao et al. (2017)	• LIWC • Hierarchical Dirichlet processes • Nonparametric clustering	• Mental health and non-mental health-related communities from LiveJournal	• 268,400 posts from mental health-related communities • 220,000 posts from non-mental health-related communities	*Not mentioned*
De Choudhury & De (2014)	• LIWC • LDA	Subreddits: • r/alcoholism • r/anxiety • r/bipolar • r/depression • r/mentalhealth • r/MMFB • r/socialanxiety • r/SuicideWatch	• 20,411 posts • 97,661 comments	• Between November 8, 2013, and December 28, 2013
Garcia et al. (2022)	• Qualitative coding	• Subreddits of 22 California campuses	• 577 posts	• Between March 16, 2020, and March, 2021
Grayson & Greene (2019)	• Graph embedding • Temporal analysis	• Various subreddits	• The 100 highest frequency participants in three temporal windows	• Between January 2014 and October 2014
Hung et al. (2020)	• LDA • Social network analysis • Sentiment analysis	• Twitter (tweets about COVID-19)	• 902,138 tweets	• Between March 20, 2020, and April 19, 2020
Iavarone & Monreale (2021)	• LIWC • Clustering analysis	Subreddits: • r/depression • r/SuicideWatch	• 25,308 posts	• Between January 1, 2014, and May 1, 2020

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Study	Method/Approach	Platform	Sample After Preprocessing	Period
Ireland & Iserman (2018)	• LIWC • Decision tree	Subreddits: • r/Anxiety • r/HealthAnxiety • r/PanicAttack • r/panicdisorder • r/PanicParty • r/socialanxiety 20 common non-anxiety subreddits as a control group	• 28,154 replies from anxiety-related subreddits • 15,102 replies from non-anxiety subreddits	*Not mentioned*
Jiang et al. (2020)	• Self-identification technique • LIWC • ANOVA • Classification experiments (BERT and REALM-like models)	Actual subreddit names are not mentioned. Data is related to the following conditions: • schizophrenia • borderline personality disorder • post-traumatic stress disorder • eating disorders • major depression disorder • general anxiety disorder • bipolar disorder • r/AskReddit as a control group	• 17.5 million posts	*Not mentioned*
Kim et al. (2023)	• LIWC • 1-way ANOVA • Clustering	Subreddits: • r/depression • r/anxiety • r/bipolar r/BPD • r/schizophrenia • r/autism • r/mentalhealth	• 587,278 posts	• Between January 2018 and December 2022
Kou et al. (2018)	• Statistical tests • Qualitative content analysis	• 14 subreddits relevant to UX	• 361 posts • 2,352 comments	• Between January 19, 2016, and August 24, 2016

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Study	Method/Approach	Platform	Sample After Preprocessing	Period
Leung & Khalvati (2022)	• LDA	Subreddit: • r/COVID19_Support	• 9,266 posts	• Between February 14, 2020, and July 19, 2021
Liu et al. (2019)	• The Hybrid Dirichlet Process Mixture Model	• Weibo	• 12,553 users • 35,200,179 messages	*Not mentioned*
Low et al. (2020)	• LIWC • Trend analysis • Wilcoxon test • LDA • Clustering	• 15 subreddits focused on specific mental health communities. • 11 non-mental health groups as control groups	*Not mentioned*	• Between 2018 and 2020
M.-L. Li et al. (2023)	• Social network analysis	• GoPro community	• A network involving 426 users and 508 links	• Between 2015 and 2022
Nguyen et al. (2017	• LIWC • LDA • Lasso – Logistic regression	• 24 active communities from Live Journal	• 5,000 posts	*Not mentioned*
Németh et al. (2021)	• LDA • Qualitative analysis	• The most popular online health forum (the name is not mentioned)	• 67,857 posts	• Between February 15, 2016, and February 15, 2019
A. Park et al. (2018)	• k-means clustering • Thematic analysis	Subreddits: • r/depression • r/PTSD (post-traumatic stress disorder) • r/anxiety	• 7,410 posts • 132,599 comments	• Between October 2015 and December 2015
J. Y. E. Park et al. (2020)	• Thematic analysis	Subreddits: • r/arthritis • r/rheumatoid	• 27 threads	• Between June 2018 and June 2019
Pirri et al. (2020)	• LDA • Social network analysis	• Twitter (tweets about World Lupus Awareness Day)	• 4,434 tweets • 2,813 users	• May 10, 2019

Study	Method/Approach	Platform	Sample After Preprocessing	Period
Sik et al., (2021)	• LDA • Qualitative analysis/Deep reading	• The most popular online health forum (the name is not mentioned	• 67,857 posts	• Between February 15, 2016, and February 15, 2019
Surian et al. (2016)	• LDA • Dirichlet multinomial mixture • Social network analysis	• Twitter (tweets about HPV vaccines)	• 284,303 tweets • 101,519 users	• Between October 1, 2013, and October 29, 2015
H. Wang et al. (2022)	• LDA • Sentiment analysis	• Weibo	• 121,633 posts	• Between November 27, 2020, and March, 30 2022
Weng and Lin (2022)	• LDA • Social network analysis	• Twitter (tweets about COVID-19)	• 120,118 tweets	• Between May 23, 2021, and May, 29 May 2021.
Yang et al. (2019)	• Gaussian mixture model • Automatic text analysis • Human annotation	• The American Cancer Society's Cancer Survivor Network	• 66,246 users • 139,807 private messages • 1,080,260 comments • 141,122 threads	• Between December 2003 and March 2018
Yin et al. (2022)	• Structural topic modelling	• Weibo	• 146,625 posts	• Between August 2021 and July 2022
Yoo et al., (2019)	• Semantic network analysis	Subreddits: • r/bipolar • r/depression	• 5,409 posts	• On May 1, 2018
Z. Wang & Zhang (2016)	• Descriptive statistics • K-W test • Correlation analysis	• 12 health-related topics from Zhihu.com	• 2,362 questions • 8,486 answers • 14,779 users	• November 2015

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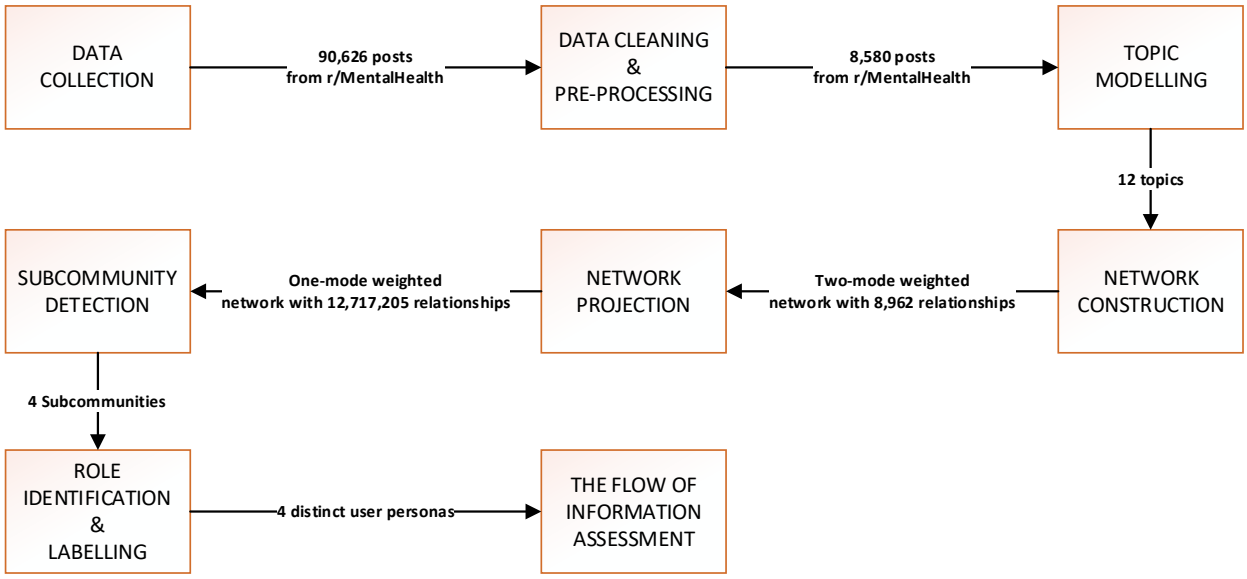

Figure 1. Summary of methodology

Alt text: A series of boxes connected by arrows to represent the sequence followed that resulted in identifying and classifying the user roles studied.

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Table 2. Topic Modelling Results

Topic	**Explanation**	**Top Words**
Suicidal Behaviour	Discussions related to suicide prevention, awareness, support, and coping strategies.	Suicide, Suicidal, Attempt, Kill, Die, Death, Commit Suicide
Mental Well-being	General conversations about mental well-being, mental illness, and self-care practices.	Mental, Health, Mental Illness, Mental Health Issues
Emotional Experience	Conversations centred around personal emotions, feelings, experiences, and self-expression.	Hate, F*ck, Sh*t, Feel, Happy
Interpersonal Connections	Discussions related to romantic relationships and friendships.	Friend, Girl, Relationship, Date, Guy, Meet, Girl Friend
Education	Conversations about experiences, memories, challenges, and transitions during the school years.	College, School, High School
Sleeping	Discussions related to sleep patterns, sleep quality, sleep disorders, and tips.	Sleep, Bed, Hour, Night, Home, Wake, Room
Video Gaming	Conversations about video games, gaming experiences, recommendations, and their impact on mental health.	Game, Video, Play, Watch, Video Games, Playing Video Games
Professional Life	Discussions related to work, job satisfaction, career choices, professional development, and work-life balance.	Job, Work, Life
Depression & Anxiety	Conversations about symptoms, treatments, coping mechanisms, and support related to depression.	Depression, Anxiety, ADHD, Disorder, Medication, OCD, Symptom, Psychiatrist
Cognitive Recall	Discussions related to memory functions, memory recall, memory improvement techniques, and personal memories.	Memory, Retention, Recall, Remember, Forget
Parenting	Conversations focused on parenting experiences, challenges, advice, and support, encompassing fathers and mothers.	Dad, Mom, Father, Mother, Parent, Sister, Child, Brother, Abuse, Childhood, Kid, Family
Panic Attack	Discussions about symptoms, treatments, coping mechanisms, and support related to panic attacks.	Panic, Attack, Panic Attack, Panic Disorder

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Table 3. Most Representative Reddit Posts

Topic	**Most Representative Posts**
Suicidal Behaviour	What is a really good reason to keep pursuing life? What is a good mindset or phrase to tell myself on a day-to-day basis? What is a method that is very arduous to carry through and gives me several chances to second guess my decision. What is something that will prevent me from doing it at a moment's notice. I do not want suicide watch bots or sympathy just good answers.
Mental Well-being	Hello, I am 16F, and well, I have struggled with mental health for so long now. But now, it is to the point where I am just pushing people away. I lost my best friends, I cry almost every day at school, I have low self-esteem, my mom does not understand me at all... I feel like I am going to snap at any second. I am sick of life. I want to shut everyone out. I just do not know what to do or who to believe anymore. I am sick of being this way. Help?
Emotional Experience	I have not cried in a long time, and I really need to let my emotions out, every time I try to cry I cannot. My eyes tear up but no actual tears/cry. I won't talk to anyone about how I am feeling because I feel like I have no reason to be upset but I am.
Interpersonal Connections	Hey! I have a friend who has been in a long, toxic, on and off relationship with a girl he still loves. For better or for worse, they broke up with the implication that it was for good. Long story short, a couple months have passed, and he is realizing that it is actually over, and he is heartbroken. This is coming on top of an already messed up life and it was in a way the straw that broke the camel's back. He has fallen deeper into depression for a while now and has suicidal ideations. He had told me things like I just want everything to stop, I just want to run away, I feel like a failure, etc. I am working on helping him get with a therapist and I am slowly making progress with that, but I was wondering if there are some other things that I could do. Maybe buying gifts?
Education	I am currently a freshman in college, and I thought I made some friends, but it feels like I am just that third wheeler or just the annoying one that everyone leaves out. Sometimes I see the people I thought I might have been friends with hangout with each other and I hear them talking about the things they did together, and I cannot help but feel left out and jealous. Even before I got into college it felt like I really could not tell who my best friends are because it always felt like they preferred to be with other people, and I was just there on the side. I do want to make more friends since I just started college here and I want to hang out with people more, but it doesn't really seem like people want to hang out with me, it just feels like everyone seemed to already find their clicks and stay with that click.
Sleeping	Without a doubt I wake up at 10:30 am. I set my alarms for 7:30 am. I have tried everything I could think of, using different alarm tones, going to bed earlier, hiding my phone so I have to get up to turn the alarm off, and I do not use my phone before I go to sleep. I do not know why this is happening to me. This problem is new for me at school. When I am home (my parents' house), I do the same thing except I wake up at 12 pm. However, at home I have come to the conclusion that I sleep later in the day to avoid a

Topic	Most Representative Posts
	person in the house. This person is not at my dorm though. So, I really don't have a reason to sleep to 10:30 am..
Video Gaming	I feel horrible, like it hurts to even breathe. I just need a distraction to burn my brain on for at least a while. I do not have friends and cannot talk to family. Thank you. I like Nintendo games and have most of the popular ones but have a couple popular PS4 games too.
Professional Life	I start in my first job tomorrow and I have a lot of anxiety hi first of all sorry if my English is not that good is not my main language I am and tomorrow is my first day of job and I am scared as fuck it is just a store job but I do not know what will I have to do or if the people will be nice to me I am scared of do something wrong or do not know how to do something I am scared every time I have to meet people but this time is different I do not want to do it wrong any advice
Depression & Anxiety	So, I really need some help. I was prescribed citalopram and quetiapine around 3 and a half years ago and have been taking them ever since (my antidepressants changed at the start, but I have solidly been on citalopram for 3 years). My doctors did not diagnose me but gave me meds, they did not refer me to therapy or anything. I have been struggling a lot with my mood swings, for the last few days I have had so much energy and had racing thoughts, loads of anxiety, being really irritable, having outbursts of anger, loud voices in my head and other stuff…
Cognitive Recall	I am 19 and I cannot remember pretty much anything from over 2 years ago. I cannot remember anything from before 16 if it was not a major event in my mind. I realized this because I was doing the RAAD-S autism assessment and the answers were about being under and over the age of 16. And I had no idea how to answer because I do not remember much of how I was. Is this concerning? I do not know how worried I should be. My parents joked about getting it checked out, but I do not know if it is actually concerning or not? Any advice or opinions?
Parenting	As a child my dad used to drink a lot and when he drunk, he was rather abusive towards me, and we always used to argue and he used to push me and he used to abuse my stepmother, I could hear it all…
Panic Attack	I (female 13) have had anxiety and suffered from severe panic attacks for almost 3 years now. I stayed in the house for about 6 months before talking to anyone about my issues. Today I finally cleaned my room and went for a walk. Its small steps that I am doing but I am proud of myself for doing it.

Table 4. Community detection results

Algorithm	Number of Communities	Modularity
Fast greedy	4	0.1719
Multilevel	4	0.2123
Walktrap	5	0.1582
Leading eigenvector	4	0.2079
Label propagation	1	0.0000
Infomap	1	0.0000

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Table 5. Community Descriptives

Community 1 Life Jugglers N=2,002		Community 2 Mindful Wellness Seekers N=2,011		Community 3 Resilient individuals N=1,614		Community 4 Emotional Connectors N=1,937	
Topics	Percent	Topics	Percent	Topics	Percent	Topics	Percent
Parenting	17%	Mental Well-being	43%	Depression & Anxiety	30%	Emotional Experience	50%
Interpersonal Connections	16%	Emotional Experience	12%	Panic Attack	25%	Interpersonal Connections	9%
Suicidal Behaviour	14%	Depression & Anxiety	7%	Emotional Experience	8%	Suicidal Behaviour	8%
Professional Life	13%	Suicidal Behaviour	6%	Mental Well-being	7%	Parenting	7%
Education	11%	Interpersonal Connections	6%	Professional Life	6%	Professional Life	6%
Sleeping	9%	Professional Life	6%	Suicidal Behaviour	5%	Education	6%
Video Gaming	5%	Parenting	6%	Parenting	5%	Sleeping	4%
Mental Well-being	4%	Education	4%	Interpersonal Connections	4%	Depression & Anxiety	4%
Emotional Experience	4%	Sleeping	4%	Education	4%	Panic Attack	2%
Cognitive Recall	3%	Panic Attack	2%	Sleeping	3%	Cognitive Recall	2%
Depression & Anxiety	2%	Video Gaming	1%	Video Gaming	2%	Video Gaming	2%
Panic Attack	2%	Cognitive Recall	1%	Cognitive Recall	1%	Mental Well-being	0%
Network Centralities							
Degree	2259.07	Degree	3898.38	Degree	3586.66	Degree	3760.07
Eigenvector	0.1764	Eigenvector	0.2711	Eigenvector	0.3082	Eigenvector	0.2524
Closeness	0.000075	Closeness	0.000083	Closeness	0.000079	Closeness	0.000084
Betweenness	1725.00	Betweenness	3270.98	Betweenness	2540.63	Betweenness	2348.62