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Multiplex Social Network Analysis to Understand the Social Engagement of Patients in Online Health Communities

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Abstract: Social network analysis has been widely used in various fields including online health communities. However, it is still a challenge to understand how patients' individual characteristics and online behaviors impact the formation of online health social networks. Furthermore, patients discuss various health topics and form multiplex social networks covering different aspects of their illnesses, including symptoms, treatment experiences, resource sharing, emotional expression, and new friendships. Further research is needed to investigate whether the factors influencing the formation of these topic-based networks are different and explore potential interconnections between various types of social relationships in these networks. To address these issues, this study applied exponential random graph models to characterize multiplex health social networks and conducted empirical research in a Chinese online mental health community. An integrated social network and five separate health-related topic-specific networks were constructed, each with 773 users as network nodes. The empirical findings revealed that patients' demographic attributes (e.g., age, gender) and online behavioral features (e.g., emotional expression, online influence, participation duration) have significant impacts on the formation of online health social networks, and these patient characteristics have significantly different effects on various types of social relationships within multiplex networks. Additionally, significant cross-network effects, including entrainment and exchange effects, were found among multiple health topic-specific networks, indicating strong interdependencies between them. This research provides theoretical contributions to social network analysis and practical insights for the development of online healthcare social networks.

Keywords: multiplex social network analysis; online health communities; exponential random graph models

MSC: 91D30

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1. Introduction

With the rapid development of social media, an increasing number of patients are turning to the Internet to seek social support [1]. Many patients may find that their family and friends are unable to provide the necessary support due to various reasons such as distance, lack of knowledge about the specific health condition, or emotional limitations [2]. In such cases, online health communities (OHCs) can fill the gap by connecting individuals with others who have firsthand experience with similar health issues [3]. OHCs offer several potential benefits for those seeking support. Firstly, these platforms significantly enhance the accessibility of support resources, overcoming barriers like geographic distance or limited availability of in-person support groups [4,5], which is particularly valuable for those with limited mobility, residing in remote areas, or encountering social stigma when seeking health-related assistance. Secondly, OHCs offer an opportunity to connect with others facing similar challenges [6]. This sense of shared experience and mutual understanding can be particularly comforting for those who may feel isolated or misunderstood within their immediate social circles [7,8]. Thirdly, in addition to emotional support, OHCs serve as platforms for the exchange of health information and coping strategies [9]. Patients can access information about diverse treatment options, self-care techniques, and valuable resources that may not be easily found elsewhere, thereby enhancing their self-management abilities [10]. Finally, online platforms provide a level of anonymity that may be particularly appealing to individuals who prefer not to disclose personal health information to their immediate social circle [11]. This anonymity allows patients to openly share their concerns, ask questions, and seek advice without revealing their identities.

Engaging in OHCs enables patients to establish support networks where they can connect with others facing similar health conditions, share experiences, provide emotional support, exchange information, and foster a sense of belonging, potentially enhancing their own health management [8,9]. Given the diverse backgrounds and health conditions of users in these online health networks, it is essential to understand which patient characteristics, such as age, gender, and online behaviors, play a key role in the formation of social relationships. Investigating these attributes can provide valuable insights into the underlying patterns and determinants that shape social connections in OHCs.

Moreover, patients in OHCs engage in diverse discussions on health topics [12], forming multiplex social networks that encompass various aspects of their illnesses. Many of them utilize online platforms to exchange information and experiences related to disease diagnosis [13], symptoms [14], and treatment approaches [15]. Additionally, some patients are dedicated to sharing valuable disease management resources [16], such as links to helpful websites, self-help materials, books, articles, and recommendations for therapists and support services. These OHCs not only provide informational support but also offer emotional support and compassion, particularly for those with chronic illnesses, severe conditions, and mental health disorders [17,18]. Furthermore, they facilitate the development of new friendships that can help to alleviate feelings of loneliness [19,20]. These interactions go beyond discussions about illnesses, encompassing various aspects of their lives, such as personal interests and hobbies [21], contributing to the development of meaningful friendships that offer a sense of belonging and support in individuals' lives. Therefore, it is essential to explore the differences in online social behaviors among patients across various topic-based networks within multiplex social networks. This can provide valuable insights into how individuals interact in specific contexts, such as discussing symptoms, sharing treatment experiences, exchanging resources, expressing emotions, and developing new friendships. Understanding this diversity and complexity of social interactions can optimize online platforms and develop tailored interventions that enhance social support and engagement within each topic-specific network.

Finally, we tried to investigate whether there exist some cross-network effects when patients participate in different health topic discussions and establish multiple social networks. This can provide valuable insights into the interconnectedness and interdependence of these diverse network relationships [22]. For instance, we wondered whether active participation in a symptom discussion network may lead to increased involvement in treatment-related interactions, suggesting that those frequently discussing symptoms are more likely to seek or offer treatment-related information and support. Another interesting aspect to consider is whether emotional support is influenced by engagement in a resource sharing network, which will help us to determine whether individuals actively involved in resource sharing also experience increased emotional support within the community. Additionally, it is worthwhile to explore how emotional support networks and friendship networks interact with other information support networks. This examination will provide insights into whether emotional support is influenced by the availability of information resources, or whether building friendships is facilitated by engagement in specific information support networks. Exploring these potential cross-network effects can reveal how interactions within one network may spill over or impact individuals' experiences and behaviors in other networks. However, the previous literature has primarily focused on single networks in isolation, without thoroughly exploring potential relationships or dependencies among networks [23]. Therefore, our examination of cross-network effects can fill this gap and offer a more comprehensive understanding of potential correlations and interdependencies within multiple social networks. Ultimately, this research can provide valuable insights into how participation in diverse health topic discussions influences the formation of relationships across these networks.

In summary, this study tried to address the following research questions using social network analysis:

RQ1: Which patient characteristics are more likely to contribute to the formation of social relationships with peers in OHCs?

RQ2: How do individual characteristics of patients play distinct roles in the formation of multiplex social networks established for discussing various health topics in OHCs?

RQ3: Do cross-network effects exist in the formation of multiplex health social networks, indicating potential correlations or interdependencies between various types of social relationships?

Over the years, many theoretical frameworks and analytical methods for studying social networks have been developed and implemented across various fields. Among these, exponential random graph models (ERGMs) [24] have emerged as a prominent and widely acknowledged approach to examining social networks, providing valuable insights into various social phenomena. ERGMs are tie-based models that aim to explain the mechanisms behind the formation of social network ties [25]. These models can incorporate different types of network configurations and assess their influence on network formation. For instance, ERGMs can consider binary, categorical, and continuous attributes of individuals involved in the network to determine whether these attributes are associated with the formation of network ties. Furthermore, ERGMs can be extended to analyze multiplex social networks, which involve multiple types of relationships or networks among the same set of actors [26,27]. This allows researchers to investigate the cross-network effects within multiplex social networks and explore how ties in one network may influence or be influenced by ties in another network. Therefore, this study employed ERGMs to conduct an analysis of multiplex social support networks in OHCs. The findings provide valuable insights into the social engagement of patients within these communities and can serve as a valuable reference for researchers and practitioners. This knowledge can help them to develop effective strategies and interventions aimed at enhancing social engagement, promoting positive social interactions, and optimizing community resources for the benefit of patients.

2. Literature Review

2.1. Social Network Theory

The ERGMs employed in this study were built upon a set of theoretical principles from social network theory, which suggest that social connections within a network not only spontaneously organize themselves, indicating there are interconnections between relationships, but also are affected by the characteristics of individuals and external factors [28]. Therefore, beyond examining the structural effects within the network itself (endogenous), we placed emphasis on the effects of actor attributes (exogenous) and investigate their significant roles in the formation of social connections within OHCs.

2.1.1. Network Structural Effects

Network structural effects in social network theory refer to the patterns and phenomena where certain relationships within a network give rise to the formation of other relationships [29]. These effects focus on the inherent interdependence and patterns of connectivity among nodes or individuals in a social network. Several key network structural effects include popularity (in-degree effects), indicating some individuals receive more connections; activity (out-degree effects), showing that some individuals initiate connections more frequently; and reciprocity, reflecting mutual connections between two individuals within a social network. In this study, we were concerned with the reciprocal effects within social support networks in OHCs. OHCs serve as knowledge-sharing platforms, promoting a mutual exchange of information that benefits both the contributors and receivers and facilitating shared knowledge for all participants [30]. Patients with similar health concerns or conditions often create a sense of empathy and understanding among members. When they receive support from others, they often feel a sense of community and mutual care, which encourages them to give back to those who have helped or supported them. Therefore, we proposed the following:

Hypothesis 1: *Patients in OHCs are likely to engage in reciprocal support behaviors.*

2.1.2. Actor Attribute Effects

Actor attribute effects in social network analysis refer to certain effects that are influenced by the characteristics of the actors involved in the network, consisting of three basic types: sender, receiver, and homophily/heterophily [29]. The sender and receiver effects only focus on one actor's attributes in a social relationship, while the homophily and heterophily effects consider the attributes of both actors involved in the dyad. The sender effect investigates how the sender's attributes affect the likelihood of initiating a social tie to another actor, and the receiver effect explores how the receiver's attributes influence the likelihood of accepting a social tie from another actor. The homophily effect (applicable to binary and categorical attributes) focuses on the tendency of actors with the same characteristics or attributes to be more likely to form social ties with each other, exploring how similarity between individuals' attributes promotes the formation of ties between them. The heterophily effect (applicable to continuous attributes), in contrast to the homophily effect, focuses on the tendency of actors with different attributes or characteristics to form social ties with each other, exploring how dissimilarity between individuals' attributes affects the formation of ties between them.

In previous studies on user behavior in OHCs, it was often believed that patients' individual attributes, such as gender and age, had a significant impact on their willingness to participate and long-term engagement in OHCs [31]. In addition, patients' online behaviors in OHCs also showed significant differences. Therefore, this study aimed to explore the impact of certain patient demographic characteristics including gender and age and their online behavior characteristics including online emotional expression, online influence, and the duration of online engagement on the development of social relationships in OHCs.

(1) Gender. Gender can play a significant role in interpersonal communication within online social networks, including OHCs [32]. Studies have shown that female patients exhibit a greater tendency to actively engage in OHCs to seek and provide social support compared to male patients [33]. This disparity may be attributed to the fact that females generally utilize healthcare services more often than males, leading to increased participation in OHCs to seek and provide support [34]. Therefore, female patients are more likely to initiate social connections within the context of social network relationships in OHCs. Additionally, traditional gender roles and societal expectations may encourage women to express their emotions and seek support from others, while men may feel societal pressure to appear self-reliant and avoid openly showing vulnerability or seeking help [35]. Thus, female patients in OHCs are more likely to seek and accept social ties initiated by others. Moreover, patients may tend to establish social support connections with others of the same gender in OHCs. This may be due to a perceived sense of understanding or shared experiences related to gender-specific health issues or simply because they find it more comfortable to interact with others of the same gender. Therefore, we proposed the following:

Hypothesis 2a: *Female patients are more likely to initiate social connections in OHCs by providing social support compared to male patients in OHCs.*

Hypothesis 2b: *Female patients are more likely to receive social ties initiated by others compared to male patients because they are more inclined to seek social support in OHCs.*

Hypothesis 2c: *Patients of the same gender are more likely to form social relationships with each other in OHCs.*

(2) Age. Older patients generally have more life experience and are more empathetic, with a stronger sense of community. The accumulated knowledge and wisdom may make them more willing and capable of offering support to others facing similar health challenges. Therefore, older patients are more likely to initiate social connections by actively providing social support to other members within the OHCs. However, compared to younger patients, older individuals may experience a greater number of health issues or chronic conditions, which can make them appear more vulnerable. Thus, older patients are more likely to receive social ties initiated by others, as they are more inclined to seek social support and other members may perceive them as more receptive to accepting social support [36,37]. Moreover, it is believed that patients of similar ages often share common health concerns and experiences related to specific stages of life or age-related health issues. This shared background can create a sense of understanding and empathy among members, making it easier for them to form social support relationships. Therefore, we proposed the following:

Hypothesis 3a: *Older patients are more likely to initiate social connections in OHCs by providing social support compared to younger patients in OHCs.*

Hypothesis 3b: *Older patients are more likely to receive social ties initiated by others compared to younger patients because they are more inclined to seek social support in OHCs.*

Hypothesis 3c: *Patients of similar ages are more likely to form social relationships with each other in OHCs.*

(3) Emotional expression. When people feel positive emotions, such as happiness, empathy, or compassion, they tend to be more prosocial and altruistic, seeking opportunities to assist others. In the context of OHCs, patients who are optimistic about their own health or treatment outcomes may be more likely to share their experiences, offer support, and give advice to others facing similar health issues [38]. Therefore, they are more likely to initiate social connections with other members within the OHCs. Conversely, individuals who express negative emotions, such as sadness, fear, or frustration, might receive more social ties initiated by other community members who might empathize or have undergone comparable challenges because their negative emotional expressions positively influence the likelihood of accepting social ties from others providing social support. [39]. Additionally, patients who express similar emotional valence online may have an increased the likelihood of forming social support connections within OHCs. This is because individuals who express emotions similarly feel more comfortable and connected to each other. When they share similar emotions, they often have common experiences, challenges, and feelings related to their health conditions, fostering companionship and mutual understanding [40]. Consequently, this similarity makes it easier for them to establish social support relationships with one another within OHCs. Therefore, we proposed the following:

Hypothesis 4a: *Patients who tend to express positive emotions are more likely to initiate social connections in OHCs by providing social support in OHCs.*

Hypothesis 4b: *Patients who tend to express negative emotions are more likely to receive social ties initiated by others because they are more inclined to seek social support in OHCs.*

Hypothesis 4c: *Patients who express similar emotional valence online are more likely to form social relationships with each other in OHCs.*

(4) Online influence. Patients with significant online influence may be seen as trustworthy and knowledgeable in OHCs [41]. As a result, they may feel a sense of responsibility to offer support, share their experiences, and provide guidance to others seeking help or information [42], making them more likely to initiate social connections with other members within the OHCs. On the other hand, because they are more visible, their posts or requests for support are more likely to be seen by others, increasing the likelihood of receiving social connections from other members who are willing to offer them help [43,44]. Moreover, it can be inferred that patients with greater disparities in online influence are more likely to provide social support to each other. This is because influential patients tend to show empathy and altruism towards less influential individuals, thereby providing them with social support. Consequently, this reciprocal dynamic fosters a higher likelihood of influential users receiving support in return from those with lower online influence. Therefore, we proposed the following:

Hypothesis 5a: *Patients with higher online influence are more likely to initiate social connections in OHCs by providing social support in OHCs.*

Hypothesis 5b: *Patients with higher online influence are more likely to receive social ties initiated by others because they are more inclined to seek social support in OHCs.*

Hypothesis 5c: *Patients with different levels of online influence are more likely to form social relationships with each other in OHCs.*

(5) Online duration. Experienced patients who have been active in OHCs for a longer time may have accumulated valuable knowledge about managing their health conditions and coping with difficulties [45]. This knowledge enhances their capacity to provide meaningful support, as they possess a deeper comprehension of community norms and the needs of fellow members. Consequently, they develop a stronger sense of community belonging, motivating them to offer valuable social support to others [46]. Therefore, they are more likely to initiate social connections with other members within the OHCs. In contrast, individuals who are relatively new to OHCs are more likely to receive social ties initiated by other members, as they tend to be more proactive in seeking support. The existing members are generally more willing to provide support to newcomers, creating a welcoming atmosphere that encourages their continued engagement in the community [47]. Additionally, it can be inferred that individuals with different durations of online engagement in OHCs tend to form social support connections, because newcomers are more likely to receive strong support from experienced members, and in turn, those experienced members willingly offer guidance and assistance to newcomers. Therefore, we proposed the following:

Hypothesis 6a: *Experienced patients are more likely to initiate social connections in OHCs by providing social support in OHCs.*

Hypothesis 6b: *Newcomers are more likely to receive social ties initiated by others because they are more inclined to seek social support in OHCs.*

Hypothesis 6c: *Patients with different durations of online engagement in OHCs are more likely to form social relationships with each other in OHCs.*

2.2. Multiplex Social Network

Multiplex social networks refer to networks where individuals are connected to each other through multiple types of relationships simultaneously, rather than being limited to a single type of connection [48]. These connections can be based on various factors such as family ties, friendships, professional collaborations, common interests, or geographical proximity [49]. In the study of multiplex social networks, focusing only on one type of relational tie can overlook important information about the overall structure and dynamics of the social network, resulting in an incomplete understanding of the complexity of social connections [29]. Conversely, considering multiple types of relationships simultaneously allows researchers to gain a more comprehensive and detailed understanding of the structure and dynamics of the social network. Many studies emphasize the importance of considering the interdependencies between different types of relationships [50], as in numerous cases these relationships are not independent but interconnected and influence each other [51]. Some scholars further propose that in multiplex social networks, various forms of interdependence exist among different types of relationships, including co-occurrence where different types of relational ties can occur between the same two individuals simultaneously, and reciprocal causality where one type of tie can act as an antecedent to another type of tie [52].

In our study, we aimed to investigate cross-network effects in OHCs where patients participate in discussions on different health topics and form multiplex health topic-specific networks. This study focused on two types of cross-network effects: entrainment effects, which refer to a tendency for different types of relational ties in two topic-specific networks to align, and exchange effects, which indicate a likelihood of different types of relational ties in two topic-specific networks to be exchanged. Understanding these effects can provide valuable insights into the interrelation and mutual dependence of various network relationships, including symptom discussions, treatment-related interactions, resource sharing, emotional support, and building friendships among patients in these networks.

It is often observed that when patients actively participate in discussions related to their health, they often develop multiple social connections across various social topic-specific networks. For instance, if two patients connect within a social network discussing the symptoms of a disease, it is highly likely that they will also connect within a network focused on treatments for that disease. Another notable finding, as indicated by certain studies, is that patients tend to combine emotional and informational support when interacting with others in OHCs [53]. This indicates that the social support networks formed for sharing health-related information may align with the networks formed for emotional support. Furthermore, the exchange of emotional support between patients has been found to contribute to the formation of friendships within these OHCs, or individuals seeking friendship within these communities are more likely to engage in emotional support exchanges, which strengthens the alignment between emotional support and friendship networks [54]. Based on these observations, we have reason to believe that multiple types of social relationships in the multiplex health topic-specific network exhibit a consistency effect. Therefore, we proposed the following:

Hypothesis 7: *There are entrainment effects across multiple health topic-specific networks within OHCs, revealing that patients who provide social support to a fellow patient in one topic-specific network are more likely to provide social support to the same patient in another topic-specific network*.

Another research question of interest is the potential exchange of relationships across multiple health topic-specific networks. It has been proved that patients who provide a certain type of social support in one topic-based network tend to receive reciprocal social support in another topic-based network. For example, if someone frequently offers valuable insights or resources concerning disease diagnosis or health management, other patients who benefit from this knowledge might provide support in return by sharing their own experiences related to the diagnosis and treatment of the same disease [55]. Similarly, when patients seek support regarding symptoms and treatment options for a particular illness, they often respond with emotional encouragement towards those assisting them [56]. Furthermore, when patients try to establish friendships through online social networks, they are more likely to actively connect with those who have provided them with informational and emotional support [57]. Based on the above, we have reason to believe that there is an exchange effect between different types of relationships within the multiplex social network formed by users engaged in OHCs. Therefore, we proposed the following:

Hypothesis 8: *There are exchange effects across multiple health topic-specific networks within OHCs, revealing that patients who provide social support to a fellow patient in one topic-specific network are more likely to receive social support from the same patient in another topic-specific network.*

3. Methods

3.1. Research Context and Data Collection

This study selected an OHC in China that is targeted toward patients with psychological disorders as the research subject. The chosen OHC serves as a convenient and efficient platform for individuals affected by psychological disorders to exchange information and emotions. Currently, this community has attracted over ten thousand registered members, with the majority of users suffering from mental and psychological disorders such as depression and bipolar disorder. Members can share their experiences, emotions, and coping strategies, which helps to alleviate feelings of isolation and foster understanding among peers. Such mutual support communities can provide a sense of belonging and may offer valuable insights and advice.

We utilized web crawling to collect publicly accessible personal information including gender and age, as well as posting details such as post content and timestamps, from user profiles on the website. After filtering out users with incomplete age and gender information, we identified 773 users who indicated in their condition descriptions that they had been clinically diagnosed with mental disorders following medical assessments at hospitals. These users collectively contributed a total of 297,052 posts, encompassing both initial discussion topics and subsequent replies. We constructed an integrated social network by analyzing the reply interactions among these participants, treating the 773 users as network nodes, and translating the reply interactions between users into directed edges. In this directed network, each edge originates from the initiator of a post and terminates at its recipient.

Subsequently, we constructed multiple social networks based on the diverse health-related topics discussed by users in the OHC. To achieve this, we employed a latent Dirichlet allocation (LDA) [58] topic model to identify distinct health-related topics from user-generated posts. The procedure can be summarized as follows: (1) All user-generated posts were subjected to preprocessing using the jieba Chinese text segmentation package in Python. This involved segmenting the text into words, removing stop words, and replacing synonyms. (2) The open-source gensim package in Python was employed to train an LDA topic model. The optimal number of latent topics was determined using the perplexity metric [58]. It was observed that as the number of topics increased, the perplexity metric tended to decrease overall. However, an excessive number of topics can lead to overfitting. It is noted that after surpassing 70 topics, the rate of decrease in perplexity started to diminish gradually. As a result, this study established 70 as the optimal number of topics. (3) Following the extraction of 70 latent topics through the LDA topic model, these topics were subsequently grouped into six major thematic categories. These categories included discussions on disease symptoms, treatments, medical resource sharing, emotional exchanges, social interactions, and friendships, as well as off-topic comments. (4) Apart from off-topic discussions, we constructed five separate social topic-specific networks for the remaining major categories, which were named *Symptom* network, *Treatment* network, *Resource* network, *Emotion* network, and *Friendship* network. Within each of these topic-specific networks, the same 773 users were considered as nodes, but the edges in the network were formed only by interactions related to that specific topic. This resulted in multiple social networks with the same node set across the five networks but featuring diverse types of relationships between the nodes.

The *Symptom* network allows patients to discuss symptoms of diseases and share personal experiences. The *Treatment* network focuses on exchanging information about medications and treatment plans. The *Resource* network allows users to share valuable information about disease diagnosis, treatment resources, and materials on self-health management. The *Emotion* network provides a platform for users to express their feelings related to their struggles with the disease and provide mutual encouragement among peers facing similar conditions. The *Friendship* network primarily focuses on providing a platform for community members to actively seek long-term companionship and support from fellow patients. It also facilitates the arrangement of offline support group meetings and the coordination of various social gatherings within the community.

In the visualization of the overall network and five topic-specific networks presented in Figure 1, we observed a consistent "core–periphery" distribution in all networks. Nodes located in the core positions connected with many other nodes, while those at the periphery formed connections with only a select few nodes, and some even remained isolated. In particular, the *Symptom* network and *Emotion* network demonstrated denser interconnectivity, forming a cohesive structure around core nodes with fewer isolated nodes at the periphery. Conversely, the *Treatment* network, *Friendship* network, and *Resource* network exhibited a comparatively looser structure, characterized by a higher presence of isolated nodes or node pairs at the periphery of the network.

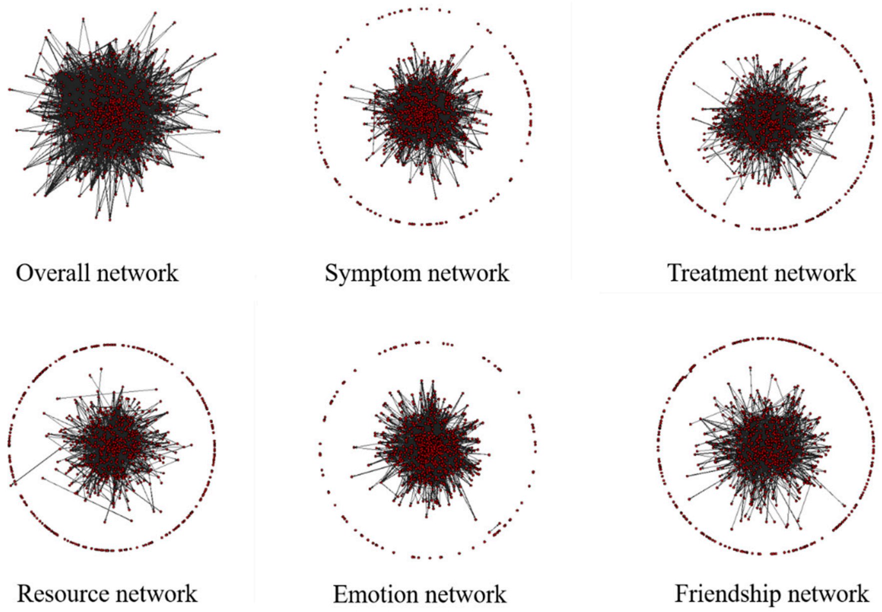


Figure 1. Illustration of the overall network and five topic-specific networks.

The statistical analysis of the number of arcs and density for the overall network and five topic-specific networks, as presented in Table 1, showed consistently low density across all networks. This suggests that social relationships in OHCs are loosely connected, aligning with the characteristics of most empirically observed online social networks. Within the five topic-specific networks, the *Emotion* network exhibited the highest count of arcs and network density, followed by the *Symptom* network. The *Treatment* network, *Resource* network, and *Friendship* network had fewer arcs and comparatively lower network densities.

Some key variables related to patient characteristics were measured to examine the actor attribute effects in our network. The variable *Gender* was measured as a dummy variable with 1 for males and 0 for females. The variable *Age* was measured as a continuous variable. We used the variable *Sentiment* to represent the user's emotional expression while engaging in the OHC. This variable was calculated using the sentiment scores from their posts. The Baidu AI Open Platform's sentiment analysis API was employed to compute the sentiment score for each post. By summing up these sentiment scores across all the posts made by the user, we derived an ultimate overall sentiment score reflecting the user's emotional valence in the OHC. We used the variable *Influence* to represent the online influence of users, which was measured using the H-index [59]. Users' posts were ranked by the number of replies received. If a user's h-th highest replied post has at least h replies, and the (h + 1)-th post has fewer than (h + 1) replies, the user's influence is rated as h. We used the variable *Duration* to represent users' engagement duration in the OHC, which was measured using cumulative online time since registration.

Table 1. Statistics of No. of arcs and density for all networks.

Network	No. of Arcs	Density
Overall	12,276	0.0206
Symptom	4483	0.0075
Treatment	2261	0.0038
Resource	2686	0.0045
Emotion	6402	0.0107
Friendship	2306	0.0039

3.2. Exponential Random Graph Models

The exponential random graph models (ERGMs) are advanced statistical models used in the analysis of social networks [25]. Unlike traditional regression methods, the ERGMs do not assume independence among network ties, making them better suited for network data analysis. The ERGMs can incorporate various patterns of ties, also known as "network configurations", and estimate how these configurations impact the formation of network ties [25]. Additionally, the ERGMs can handle multiple types of actor attributes (binary, categorical, continuous) and dyad-specific covariates, and determine whether these attributes influence the creation of network ties. Moreover, the ERGMs can be applied to diverse types of networks with different types of nodes and relationships and can even model two separate networks simultaneously. This makes the ERGMs particularly suitable for studying complex social networks.

We used the notation and terminology described by Robins et al. (2007) [25]. For each pair i and j of a set N of n actors, X_{ij} is a network variable that represents a tie between actor i and actor j (X_{ij} = 1 if there is a tie from actor i to actor j, and 0 otherwise). These ties are represented in an $n \times n$ adjacency matrix (n is the number of actors in the network), which is denoted as X. We specify x_{ij} as the observed value of X_{ij}, and x denotes a matrix of observed ties of the network. A general form of the ERGMs can be expressed as follows:

$$Pr(X = x) = \frac{1}{\kappa} \exp \textstyle\sum_A \theta_A z_A(x) \tag{1}$$

where:

- $Pr(X = x)$ represents the probability of the network variable X taking the observed value x;
- A defines the network configurations that are patterns of social network ties assumed to represent underlying social processes or mechanisms of network tie formation;
- $\sum_A$ is the summation over all different configuration types in the model;
- $z_A(x)$ is the network statistic corresponding to the network configuration of type A;
- θ_A is the parameter corresponding to the configuration of type A;
- κ is a normalizing constant to ensure that the sum of probabilities in Equation (1) over all possible x equals 1; that is,

$$\kappa = \textstyle\sum_{x \epsilon X} \exp \sum_A \theta_A z_A(x) \tag{2}$$

The ERGMs were subsequently expanded to analyze multivariate social network [60], where a set of M networks was defined on a set of n nodes, x was a set of tie variables (x_{ijm}, mϵM), and the networks can be represented by an "n by n by M" adjacency array. In the directed networks, $x_{ijm} = 1$ if there is a tie sent from node i to node j in network m; otherwise, $x_{ijm} = 0$. The graph statistics $z_k(x)$ were defined both within and across ties from different types of networks. Thus, they were more complex than the graph statistics for single networks and had the following general form:

$$z_k(x) = \sum_{A \epsilon A_k} \prod_{(i,j,m) \epsilon A} x_{ijm} \tag{3}$$

where A_k is the collection of isomorphic configurations A of tie variables.

In this study, we focused on the basic specifications of a multiplex social network model applied to networks that incorporate two distinct types of connections within a shared set of nodes. The ERGM specifications consisted of within-network effects which defined graph configurations using ties from a single network and cross-network effects where graph configurations were defined involving ties from two networks. In this study, the within-network effects included network structural effects and actor attribute effects. Let $Y = \{Y_i\}$ be a set of variables representing the attribute value for node i, where $0 < i \leq n$, and $y = \{y_i\}$ be its realization. A general form of the ERGMs for single networks can be expressed as follows:

$$Pr(X = x | Y = y) = \frac{1}{\kappa} \exp \sum_{Q,\Lambda} \{\theta_Q Z_Q(x) + \theta_\Lambda Z_\Lambda(x, y)\} \tag{4}$$

where:

- Q is a network configuration of type Q comprising tie variables that are conditionally dependent given the rest of the network;
- Λ is a joint attribute-network configuration comprising tie variables as well as nodal attribute variables;
- $Z_Q(x)$ are sufficient statistics representing the network endogenous effects;
- θ_Q is the vector of parameters corresponding to the graph statistics without nodal attributes;
- $Z_\Lambda(x, y)$ are sufficient statistics for the interactions between the network and nodal attributes;
- θ_Λ is the vector of parameters corresponding to the graph statistics representing the interaction between network tie variables X_{ij} and nodal attributes Y_i.

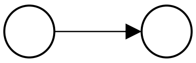
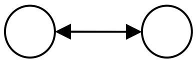
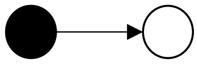
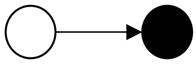
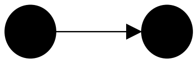
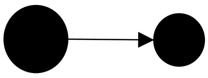
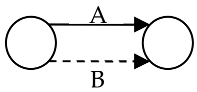
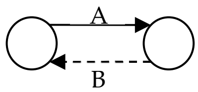
Our main focus is on two types of cross-network effects for associations between two directed networks at the dyadic level: entrainment effects and exchange effects. Let us consider two directed networks, A and B, with tie variables represented as x_{ijA} and x_{ijB}. The entrainment effect ("ArcAB") represents the extent to which the two network ties align within the dyad (i.e., both ties in network A and B are directed from node i to node j), whereas the exchange effect ("Reciprocity AB") represents the extent to which the dyad exchanges ties of different types (network A from node i to node j, and network B from node j to node i). The relevant statistics can be calculated as follows:

$$z_{\mathrm{Arc}AB}(x) = \sum_{i,j} x_{ijA} x_{ijB} \tag{5}$$

$$z_{\mathrm{Reciprocity}AB}(x) = \sum_{i,j} x_{ijA} x_{jiB} \tag{6}$$

to provide a clearer understanding of the application of the ERGMs in analyzing multiplex social networks and validate our hypotheses, we offer a visual representation illustrating both within-network effects and cross-network effects incorporated into the model. The detailed specifications of the ERGMs are presented in Table 2. In our ERGM specifications, we included the reciprocity parameter as part of network structural effects, in addition to the arc parameter, to test hypothesis H1. We then incorporated three basic actor attribute effect types: sender, receiver, and homophily/heterophily. These effects were applied to each individual's demographic attributes and online behavioral features, including *Gender*, *Age*, *Sentiment*, *Influence* and *Duration*. In total, our model comprises fifteen actor-relation effects. Specifically, there are five sender parameters for the five users' individual attributes to test H2a, H3a, H4a, H5a, and H6a, and five receiver parameters for these same individual attributes to test H2b, H3b, H4b, H5b, and H6b. A homophily parameter for *Gender* is included in the model to test H2c, while four heterophily parameters for the remaining four attributes are included to test H3c, H4c, H5c and H6c. Furthermore, we applied multivariate ERGMs to analyze the multiplex social topic-specific networks, specifically incorporating entrainment and exchange effects in order to test H7 and H8.

Table 2. Summary of network configurations included in ERGMs.

Network Effect	Configuration	Statistic	Hypothesis
Network structural effects			
Arc		$\sum_{i,j} x_{ij}$	
Reciprocity		$\sum_{i,j} x_{ij}x_{ji}$	H1
Actor attribute effects			
Sender effects		$\sum_{i,j} y_i x_{ij}$	H2a, H3a, H4a, H5a, H6a
Receiver effects		$\sum_{i,j} y_j x_{ij}$	H2b, H3b, H4b, Hb, H6b
Homophily effects		$\sum_{i,j} x_{ij}y_i y_j$	H2c
Heterophily effects		$\sum_{i,j} \lvert y_i - y_j \rvert x_{ij}$	H3c, H4c, H5c, H6c
Cross-network effects			
Entrainment effects		$\sum_{i,j} x_{ijA}x_{ijB}$	H7
Exchange effects		$\sum_{i,j} x_{ijA}x_{jiB}$	H8

4. Results

This research employed the Metropolis–Hastings algorithm, which is a widely used Markov Chain Monte Carlo (MCMC) method, along with maximum likelihood estimation to estimate the parameters of the applied ERGM. The procedure involves iteratively simulating the creation of random networks, comparing them with the actual networks, gradually improving the model's parameters, and repeating this process until the simulated network closely approximates the actual network and the parameters reach stability. This approach results in an estimated set of model parameters that align with the actual observations. The model evaluation is conducted through a comparison of models using the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), with smaller values of BIC and AIC indicating a better fit of the model.

All models successfully converged and fitted the data well. The parameter estimation results for the overall networks were shown in Table 3. Three models with different parameters were constructed to demonstrate the significance of these effects and whether they changed with the inclusion of additional effects. Model 1 only included network structural effects, while Model 2 added users' demographic attributes to validate actor attribute effects. Model 3 extended this by incorporating users' online behavioral characteristics to further investigate actor attribute effects.

Table 3. Parameter estimates for the overall network.

Parameter	Model 1			Model 2			Model 3		
	Estimate	SE	*p*-Value	Estimate	SE	*p*-Value	Estimate	SE	*p*-Value
Network structural effects									
Arc	−4.252	0.011	<0.001	−5.529	0.031	<0.001	−6.275	0.065	<0.001
Reciprocity	3.550	0.031	<0.001	3.352	0.032	<0.001	1.717	0.045	<0.001
Actor attribute effects									
Gender-Sender				0.113	0.019	<0.001	0.245	0.023	<0.001
Gender-Receiver				−0.235	0.019	<0.001	−0.055	0.023	0.015
Gender-Homophily				0.044	0.015	0.004	0.061	0.021	0.003
Age-Sender				3.026	0.067	<0.001	1.364	0.084	<0.001
Age-Receiver				1.653	0.069	<0.001	0.476	0.084	<0.001
Age-Heterophily				−1.228	0.069	<0.001	−1.347	0.085	<0.001
Sentiment-Sender							1.139	0.068	<0.001
Sentiment-Receiver							−0.581	0.069	<0.001
Sentiment-Heterophily							−1.131	0.076	<0.001
Influence-Sender							7.133	0.171	<0.001
Influence-Receiver							12.395	0.168	<0.001
Influence-Heterophily							−7.167	0.134	<0.001
Duration-Sender							3.335	0.140	<0.001
Duration-Receiver							−0.132	0.142	0.353
Duration-Heterophily							−0.218	0.125	0.083
AIC	110,799			106,854			84,459		
BIC	110,822			106,945			84,651		

Note: SE = standard error.

As shown in Model 1, both the arc and reciprocity parameters were significant. The parameter *Arc* was significantly negative, indicating a lower network density, which aligned with previous statistical findings regarding the actual network. The parameter *Reciprocity* was significantly positive, indicating the presence of a significant reciprocity effect within the social network. Users in the OHC tended to respond after receiving social connections from others, thus forming a mutually beneficial relationship. Therefore, Hypothesis 1 was supported.

After incorporating the effects of gender and age as demographic attributes into Model 2, we observed a decrease in both the AIC and BIC values. This indicated that the incorporation of demographic attributes resulted in an improved fitness of the model. In the analysis of gender-related attribute effects, we observed significant differences in the sender and receiver effects of gender. The sender effect of *Gender* was significantly positive, indicating that males tended to provide social support to others more frequently, while the receiver effect of *Gender* was significantly negative, meaning that females were more likely to receive social support from others. Additionally, we observed a positive and significant homophily effect of *Gender*, indicating that users of the same gender were more likely to form social relationships. Therefore, Hypothesis 2a was rejected, while Hypotheses 2b and 2c were supported. In terms of age-related attribute effects, we observed that the sender and receiver effects of *Age* were significantly positive, while the heterophily effect of *Age* was significantly negative. This indicated that compared to younger users, older users were not only more willing to actively provide social support but also received more social support from others. Additionally, users with closer ages were more likely to provide social support to each other. Therefore, Hypotheses 3a, H3b, and H3c were supported.

After integrating network structural effects and all actor attribute effects in Model 3, we observed a significant decrease in both the AIC and BIC values compared to previous models. This indicated that the full model accounting for users' online behavioral characteristics provided a better fit with the actual data. This highlighted the importance of users' online behavioral characteristics in influencing the formation of social relationships in the OHC.

The results for actor attribute effects of users' online emotional expression showed that the sender effect of *Sentiment* was significantly positive, but the receiver effect of *Sentiment* was significantly negative, suggesting that users with positive emotional tendencies online were more likely to provide social support, while those who tended to express negative emotions were more likely to receive social support. Additionally, the heterophily effect of *Sentiment* was significantly negative, indicating that users preferred to provide social support to fellow patients who expressed similar emotional valence. Therefore, Hypotheses 4a, 4b, and 4c were supported.

The results for actor attribute effects of users' online influence showed that the sender and receiver effects of *Influence* were both significantly positive, indicating that users with higher online influence were more willing to provide social support to others and received social support. Additionally, a significant and negative heterophily effect of *Influence* suggested that there was a greater probability of forming social support connections among patients with similar levels of online influence. Therefore, Hypotheses 5a and 5b were supported, while Hypothesis 5c was rejected.

The results for actor attribute effects of users' online duration indicated a significant positive sender effect of *Duration*, suggesting that experienced patients who had spent longer duration participating in the OHC were more likely to provide social support to others. However, the receiver effect and heterophily effect of *Duration* were both not statistically significant, indicating that there was no empirical evidence to conclude that the likelihood of users receiving social support was influenced by the duration of their engagement in the OHC. Similarly, there was no evidence supporting a correlation between the duration of online participation in health communities and mutual social support among users. Therefore, Hypothesis 6a was supported, while Hypotheses 6b and 6c were rejected.

In order to further explore the differences in factors influencing the formation of social relationships among users within the multiplex social network emerging from discussions on different topics, we employed the ERGMs to model the five topic-specific networks that were previously established. The model specifications for each of the five topic-specific networks remained consistent with the overall model developed earlier, incorporating the same network structural effects and actor attribute effects as employed in the overall network modeling process. The results of the parameter estimation for the five topic-specific networks were presented in Table 4.

Table 4. Parameter estimates for five topic-specific networks.

Parameter	Symptom	Treatment	Resource	Emotion	Friendship
Network structural effects					
Arc	−6.752 ***	−6.853 ***	−7.827 ***	−6.873 ***	−8.592 ***
Reciprocity	1.595 ***	2.425 ***	1.381 ***	1.685 ***	1.244 ***
Actor attribute effects					
Gender-Sender	0.430 ***	0.322 ***	0.378 ***	0.148 ***	0.403 ***
Gender-Receiver	−0.030	−0.060	0.177 ***	−0.248 ***	0.130 *
Gender-Homophily	0.052	0.054	−0.022	0.099 ***	0.009
Age-Sender	1.574 ***	2.356 ***	0.933 ***	1.161 ***	1.362 ***
Age-Receiver	0.813 ***	0.968 ***	0.580 ***	0.354 **	0.101
Age-Heterophily	−1.714 ***	−1.799 ***	−1.329 ***	−1.391 ***	−1.980 ***
Sentiment-Sender	0.747 ***	0.106	0.898 ***	1.326 ***	1.567 ***
Sentiment-Receiver	−1.348 ***	−1.396 ***	−0.688 ***	−0.372 ***	0.028
Sentiment-Heterophily	−1.233 ***	−1.611 ***	−1.407 ***	−1.265 ***	−0.435 **
Influence-Sender	6.969 ***	5.028 ***	7.701 ***	7.597 ***	6.993 ***
Influence-Receiver	11.142 ***	8.865 ***	11.046 ***	12.219 ***	11.342 ***
Influence-Heterophily	−7.219 ***	−5.616 ***	−7.525 ***	−7.404 ***	−7.257 ***
Duration-Sender	1.790 ***	1.713 ***	2.341 ***	2.567 ***	1.587 ***
Duration-Receiver	−1.731 ***	−2.004 ***	0.879 ***	−0.400 *	−0.805 ***
Duration-Heterophily	1.655 ***	1.543 ***	0.610 ***	0.262	1.800 ***
AIC	40,134	24,455	23,080	49,575	21,842
BIC	40,326	24,647	23,272	49,767	22,034

Note: ***, **, *, and no * represent $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Approximate Wald Test was used (Parameter estimate is greater than two times the standard error in absolute value).

In terms of network structural effects, we found significant negative arc parameters and positive reciprocity parameters across the five topic-specific networks, aligning with the overall network parameter estimates. Consequently, we focused on analyzing how individual attributes, such as user demographics and online behavior, impacted the formation of network relationships across these various topic-specific networks.

The parameter estimates shown in Table 4 regarding actor attribute effects on the five topic-specific networks revealed some distinct differences in these effects among diverse networks, despite the general consistency observed for most actor attribute effects across these networks. The significant differences were found in the following aspects: (1) Gender effects. In terms of receiver effects of gender, the *Emotion* network was the only one that showed a significant negative effect, aligning with the overall network. Conversely, in the *Resource* and *Friendship* networks, the receiver effects of gender were significantly positive, while they were not significant in the *Symptom* and *Treatment* networks. As for the homophily effects of gender, only the *Emotion* network exhibited a significant positive effect, aligning with the overall network, whereas the other four topic-specific networks did not show statistically significant gender homophily effects. (2) Age effects. In terms of the receiver effects of age, positive and significant effects were found in all topic-specific networks, aligning with the overall network, except the *Friendship* networks where the receiver effect of age did not show significance. (3) The effects of online emotional expression. We identified two areas where certain networks differed significantly from others. The first was in the *Treatment* network, where the sender effect of online emotional expression lacked statistical significance, and the second was in the *Friendship* network, where the receiver effect of online emotional expression was also not statistically significant. (4) The effects of online duration. In terms of the receiver effects of online duration, the Resource network was the only one that demonstrated a significant positive effect, whereas the remaining four networks showed significant negative effects. Additionally, positive and significant heterophily effects of online duration were found in all topic-specific networks except the *Emotion* network where the heterophily effect did not show significance.

Based on the above analysis, we can conclude that users' individual attributes, including demographic factors like gender and age, as well as online behavioral characteristics such as emotional expression and engagement duration, have significant differences in their impacts on the formation of social relationships within multiplex social networks formed through discussions on various health topics.

We conducted additional analyses to determine whether cross-network effects occur when patients discuss various health topics and establish multiple social networks. Our examination focused on two categories of cross-network effects within the multiplex social network in the OHC: entrainment effects and exchange effects. In this modeling specifications, we expanded upon the baseline Model 1, which only accounted for network structural effects, by incorporating entrainment effects and exchange effects as the specific cross-network effects of interest. The results are summarized in Table 5.

The results for entrainment effects revealed that there were significant and positive entrainment effects between any two of the five health-related topic-specific networks, indicating that multiple types of relationships within the multiplex topic-specific network tended to align with each other. When one patient started discussing a particular health topic, he or she was also likely to engage in discussions on other health topics, providing multi-dimensional social support simultaneously. Therefore, Hypothesis 7 was supported.

In addition, the results for exchange effects revealed that there were significant and positive exchange effects between any two of the five health-related topic-specific networks, meaning that individuals providing social support to fellow patients in one topic-specific network were more likely to receive reciprocal support from the same patients in other topic-specific networks. These cross-network exchange effects indicated that patients tended to reciprocate support across diverse health topics, thereby developing diverse social relationships within the OHC. These findings emphasized the interconnected and reciprocal nature of multiplex social topic-specific networks in OHCs. Thus, Hypothesis 8 was supported.

Table 5. ERGM estimates of cross-network effects for two topic-specific networks.

Cross-Network Effects	Entrainment Effect			Exchange Effect		
	Estimate	SE	t-Ratio	Estimate	SE	t-Ratio
Symptom—Treatment	4.335 *	0.064	0.026	0.787 *	0.121	0.058
Symptom—Resource	3.944 *	0.064	0.03	0.548 *	0.097	0.023
Symptom—Emotion	4.125 *	0.043	0.027	0.679 *	0.077	0.064
Symptom—Friendship	3.901 *	0.069	0.086	1.155 *	0.097	−0.062
Treatment—Resource	3.376 *	0.082	−0.039	0.750 *	0.112	−0.044
Treatment—Emotion	3.732 *	0.063	0.056	0.622 *	0.091	0.055
Treatment—Friendship	3.344 *	0.081	0.09	0.851 *	0.122	−0.025
Resource—Emotion	4.110 *	0.052	0.044	1.117 *	0.082	−0.009
Resource—Friendship	3.849 *	0.068	0.098	1.238 *	0.112	−0.004
Emotion—Friendship	3.855 *	0.066	0.062	1.305 *	0.085	0.009

Note: SE = standard error. Effects with * are significant using the Approximate Wald test (Parameter estimate is greater than two times the standard error in absolute value).

We further conducted goodness-of-fit tests to examine whether the ERGMs in this study fitted the actual network well. Specifically, we focused on four key graph features of directed networks: the distributions of out-degree, in-degree, shared partner distributions, and geodesic distances representing the pairwise shortest distances between the nodes. The results are presented in Figure 2, where four plots are employed to assess the quality of fit for the four network statistics. In each plot, the solid line represents a given network statistic from the observed network and the boxplots represent the same statistic from the 100 simulated networks including the median and interquartile range, while the gray lines indicate the 95% confidence interval of simulated network measures. As illustrated in Figure 2, the goodness of fit for the four network statistics revealed a lack of significant difference between the actual and simulated networks, indicating that the ERGMs applied in our study effectively captured the characteristics of the observed data.

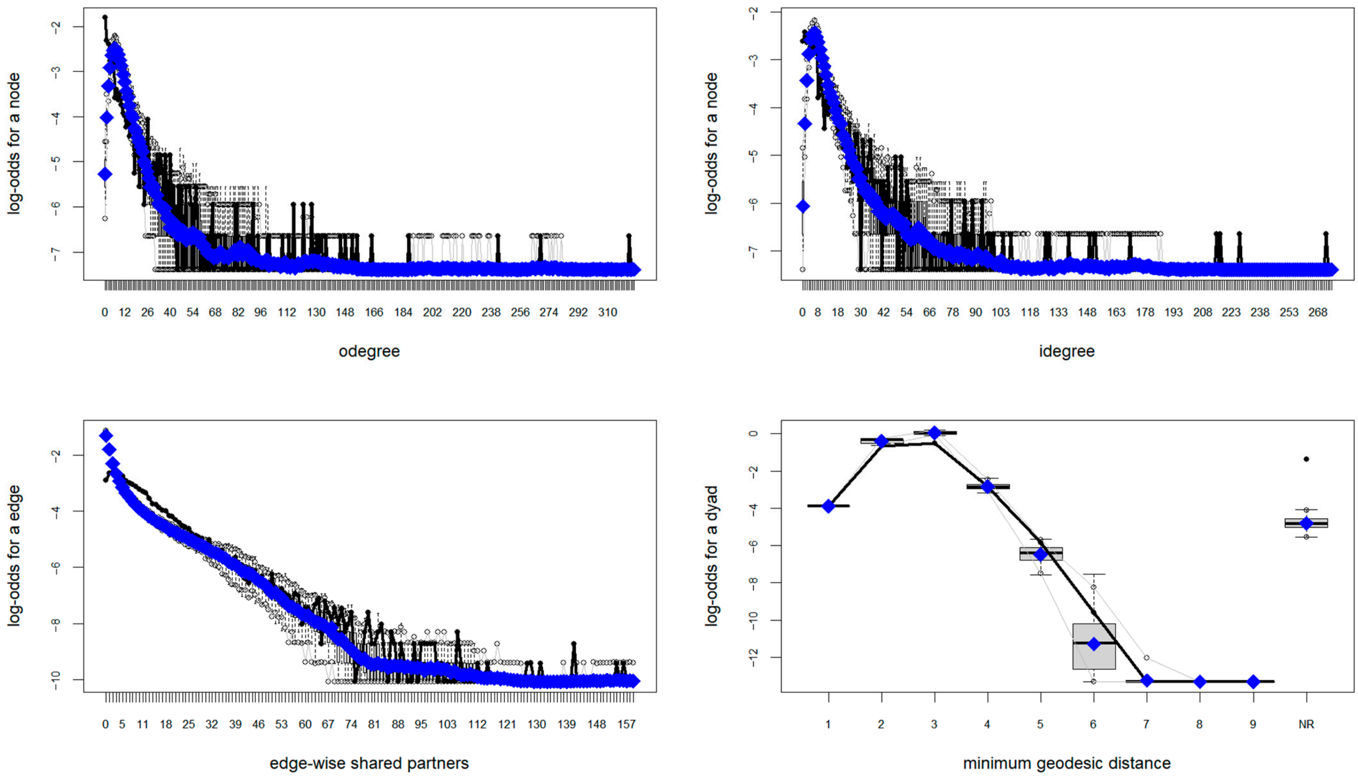


Figure 2. Goodness-of-fit plots for the ERGMs.

5. Conclusions

In recent years, social network analysis methods have been widely developed and applied in various fields, including online social networks in OHCs. However, due to the complexity of the formation of social networks, it remains challenging to fully understand how patients' individual characteristics and online behaviors impact the development of these networks in the healthcare field. In particular, users participating in OHCs often focus on different health-related topics based on their unique interests and participation purposes, resulting in multiplex social topic-specific networks. Further research is necessary to examine whether the factors that influence the formation of various types of social relationships in multiple social networks are different and explore whether there are certain interconnections between various types of social relationships in multiplex social networks.

To address these issues, this study employed an exponential random graph model to model the multiplex social networks within OHCs. Through empirical research, some valuable findings were obtained: (1) Firstly, we discovered that patients' demographic attributes, such as age and gender, along with their online behavioral features, including online influence, emotional expression, and participation duration, significantly impacted the formation of social relationships within the OHC. (2) Moreover, our further investigation revealed that these patients' characteristics had significantly different effects on the formation of various types of social relationships within the multiple social networks created by patients participating in different topic discussions in the OHC. (3) Additionally, we found that there were significant cross-network effects within the multiplex social networks in the OHC. These cross-network effects included both the entrainment effects and exchange effects, indicating strong interdependencies between the formation of these different topic-specific networks.

This research makes several theoretical contributions and have practical implications in the field of social network analysis. This study contributes to the development of social network analysis theories and provides valuable guidance for future research on the formation process of online healthcare social networks. We conducted a comprehensive investigation into the formation of multiplex topic-specific networks in OHCs, exploring the specific factors that influence the development of diverse social connections within these networks and examining the interconnectedness and interdependencies of different types of social relationships within these networks. These theoretical explorations provide valuable insights into understanding the complexities and underlying mechanisms of multiplex online social networks. Our findings have valuable implications for the designers and administrators of online healthcare platforms. They provide valuable insights into the complexity and interconnectedness of multiplex healthcare social networks, enabling a deeper understanding of patient characteristics and their role in creating multiplex topic-specific networks. These insights can help platform designers and managers to better serve users and promote the improved development of online healthcare social networks.

This study has some limitations that require further discussion. Firstly, it is important to note that the inferences drawn from the statistical analysis in this paper are limited to the specific patient population within this OHC. Given that the data were not collected through a proper random mechanism, the generalizability of our findings beyond this population is constrained. Secondly, we only focused on one specific disease forum as the source of experimental research data. Due to the significant differences in symptoms, treatments, and patient experiences across various diseases, health topics related to these diseases also vary significantly, resulting in distinctly different social networks formed around these topics. Therefore, the findings of this study may not be directly applicable to healthcare social networks related to other diseases. To conduct differential analysis and make more accurate and generalizable conclusions about the features of online healthcare social networks, further data collection from online health forums focusing on other diseases is necessary to understand how online healthcare social networks differ across different diseases. Lastly, in our examination of how user demographic attributes impact the formation of online healthcare social networks, we only considered a limited set of demographic attributes like gender and age. It is possible that other important attributes, including geographic location, health conditions, and the level of health literacy, could have a significant influence on network formation and the subsequent analysis of multiplex topic-specific networks. Further investigation and identification of these significant attributes are needed for future studies.

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