Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-02703-4 OPEN

Exploring user interaction patterns in an online physician interactive community based on exponential random graph models

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The online physician interactive community (OPIC) is a platform designed for medical workers to discuss medical issues. Physician users can create content in OPIC by posting and replying to posts to discuss the solutions of medical problems with other users. The OPIC plays an important role in bringing together physicians from different medical specialties and disseminating medical experience. However, most OPIC users are not very active in replying to posts, which makes it difficult to fulfill users' needs for medical information exchange and the development of OPIC is difficult. Current research has given little attention to the communication of physician users in the OPIC. It is necessary to examine how reposting links are established between users in OPIC. This study builds a user interaction network based on the perspective of social network analysis using user repost data from a well-known OPIC in China. Then, an exponential random graph model (ERGM) was applied to quantitatively analyze this user interaction network. Some reposting patterns among OPIC users were discovered. There is significant reciprocity in OPIC of reposting interactions between users. Users with homogeneous characteristics in terms of professional status, community honor status, and geographic location were more likely to interact with each other. In addition, users who added a profile, had a higher level of social effort, and generated more neutral content were more likely to receive responses from others. This study reveals the interaction patterns between physician users in OPIC, which enriches the related research within the OPIC domain and helps to improve communication between users in OPIC.

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Introduction

Health issues have consistently garnered public attention. With the increasing popularity of social media, people are searching for and discussing health information not only offline but also online (Zhang et al., 2020). Physicians are a special group in health information searches because they are often seen as health information providers and are supposed to export health knowledge (Zhou et al., 2019). Despite the fact that physicians have more health knowledge than does the general population, they actually have a more urgent need for health information due to their professional needs (Magrabi et al., 2005). However, owing to the limitations of the profession itself and the medical specialization of the issue, physicians are less free and have more difficulty receiving a response when seeking health care information from others. The emergence of OPIC provides another way for physicians to seek health knowledge.

The OPIC is a platform designed for medical workers to discuss medical issues together. Medical users can communicate across hospitals and departments in OPIC (Rolls et al., 2016). OPIC has been shown to improve knowledge sharing (Barnett et al., 2012) and learning performance (Bientzle et al., 2019) among medical workers. There is a relatively free online communication atmosphere and a large number of physician users from different departments around the world in OPIC. These factors make it easier for physicians to obtain help from their peers and increase the likelihood of resolving medical issues. However, users are generally less motivated to reply to posts in OPIC, which is detrimental to the communication of medical issues among physician users and the development of the OPIC.

The current study conducted in OPIC focuses on analyzing the various characteristics of posts (Dieleman and Duncan, 2013; Rooderkerk and Pauwels, 2016) but rarely digs into the relationships between users in OPIC from a social analysis perspective. This study addresses this research gap. Reposting in OPIC boils down to an informational interaction between two users, the poster and the reposter. Each repost corresponds to a pair of user interactions, which ultimately forms a user interaction network in the OPIC. The purpose of this study is to analyze the user interaction network in OPIC and reveal the interaction patterns between users.

Several studies have been conducted to analyze user interaction networks in other online communities. In the user interaction networks of these studies, the nodes are users, while the edges are "like" (Song et al., 2015) or "repost" (Yang et al., 2017) connections between two users. When analyzing user interaction networks, these studies have considered reciprocal features of user interactions. In addition, they considered the effects of different user attributes, such as activity (X. Liu et al., 2020), location (Deng et al., 2023) and learning progress (Wu and Wu, 2021), as well as the topic and sentiment of the user-generated content (Yang et al., 2017), on the interactions between users.

Based on previous studies, this study established a user interaction network based on reposting data from the OPIC. By analyzing this network in terms of network structure effects, user attribute effects and sentiment effects using exponential random graph models (ERGMs), some patterns of reposting between users were found in OPIC. Several new user attribute effects on user interactions in OPIC, such as professional status and community honorary status, are revealed. This paper is organized as follows. In the next section, a series of hypotheses for the interaction patterns between users in OPIC are presented in terms of network structure, user attributes and emotions. The Materials and methods section introduces the data sources of this study, the method used to quantify user attributes, and the ERGM. Section 4 tests the hypotheses and explains the results. Section 5 summarizes the entire paper and describes its contributions and shortcomings.

Research hypotheses

Reciprocity is an important feature of network structure effects. In social networks, reciprocity is the social outcome of individuals choosing to give back to others (Robins et al., 2007). People have certain expectations of reciprocal relationships, as they hope that after helping others, they will be helped by others in the future (Kang et al., 2017; Kapoor et al., 2018). Some studies have also indicated that people who receive help from others tend to repay others (Feng & Ye, 2016; Lakhani and von Hippel, 2003). Users in OPIC have medical expertize and the ability to support each other when discussing medical issues. There are so many threads in OPIC that users generally reply only to those in which they are particularly interested. When a user receives a reply from another user, he or she may be very willing to engage in further discussion with that user on those medical issues, resulting in reciprocal exchange. Therefore, we propose the following hypothesis:

H1: Users tend to reciprocate interactions in OPIC.

In addition to network structural characteristics, node attribute characteristics are also important for network formation. A node contains multiple attributes, and these attributes may play different roles in the network. In this study, node attributes correspond to user attributes in OPIC.

Different nodes in a network may exhibit similar characteristics for the same attribute. Previous research has indicated that when two nodes in a network have homogeneous attributes, these two nodes are more likely to be connected (McPherson et al., 2001). With respect to OPIC, physician users with certain similar characteristics may also be more likely to build trust and communicate with each other (Chang et al., 2013; Ruhela et al., 2016). OPIC users have different professional identities and may be practicing physicians, medical students, or nurses, among others. Communication between users with different professional identities may be blocked due to differences in perception, etc. (Elder et al., 2003; Rikers et al., 2004). Users with the same professional identity may communicate more smoothly because of similarities in medical experience and topics of interest. Therefore, users who are homogeneous in terms of their professional identity are more likely to communicate with each other in OPIC. Based on the above considerations, the following hypothesis is proposed:

H2: Users with the same professional status are more likely to interact with each other in OPIC.

Professional statuses are acquired in real life, while physician users can also acquire virtual statuses in OPIC. The OPIC awards community honorary status to outstanding users based on their participation in posting and replying to posts in the community. Community honorary status is a special identification that reflects the user's virtual status in the community (Marbach et al., 2019; Shao et al., 2022). Some studies have indicated that people are also concerned about status in the virtual environment of online communities (Gallus, 2017; Levina and Arriaga, 2014). People are motivated to seek higher status, and users with high status are more cautious about the status they acquire (Ma et al., 2022). In this sense, users with community honorary status in OPIC may be more popular, and many users, including not only regular users but also users who also have community honorary status, may want to connect with them. The eventual trend within OPIC may be that users with community honorary status interact more with each other, while the remaining users (without honorary status) interact more with each other. Therefore, the following hypothesis is proposed:

H3: Users with the same community honorary status tend to interact with each other in OPIC.

Among user attributes, the location of the user is also important. Different regions have different conditions and environments, which may also have an impact on communication between people (Deng et al., 2023; Wimmer and Lewis, 2010). Provinces in China differ in health resource allocation efficiency (Sun and Luo, 2017), which may lead to different medical problems faced by physicians in different regions when carrying out their daily consultations. Regions with similar health resource allocation efficiencies have broadly comparable medical capacities. The medical problems encountered by physicians in these regions may have certain commonalities, and it may be easier for these physician users to discuss ideas together in OPIC. Therefore, the following hypothesis is formulated:

H4: Users who are in regions with similar health resource allocation efficiency are more likely to interact with each other in OPIC.

Users in OPIC can edit their profile on the homepage as they wish. Different users have different attitudes toward their profiles. Some users disclose their names, hospitals, and specialties in detail, while others do not add anything to their profiles. Personal profiles in the platform are nonmandatory information, and users who are willing to edit their personal profiles have a high degree of self-disclosure. Several studies have indicated that users' self-disclosure in social media has a positive impact on the scale (Kwak et al., 2014) and depth (Ljepava et al., 2013) of their socialization. People's self-disclosure also brings them closer to other people psychologically, thus facilitating cooperation between them (Ma et al., 2024). In the medical field, physicians' self-disclosing behavior toward patients facilitates a good therapeutic relationship (Datta-Barua and Hauser, 2023). OPIC users who have a personal profile added may also be more likely to make other users feel close and willing to communicate with them. Therefore, the following hypothesis is formulated:

H5: Users who add a personal profile are more likely to receive responses from other users in OPIC.

The impact of effort on performance has been demonstrated in marketing studies (VandeWalle et al., 1999). In the medical field, physician effort is also often linked to patient decision-making (Deng et al., 2019). In OPIC, each user puts a different amount of effort into socializing. Some users often initiate social contact with other users, while others may rarely engage in discussions with people in OPIC. Within the online community context, users who exert more social effort, such as by receiving interactive feedback from others, are more likely to be rewarded. Based on this, the following hypotheses are proposed in this study:

H6: Users with higher levels of social effort are more likely to receive responses from other users in OPIC.

The popularity of a user in an online community can generally be categorized into two types: the attractiveness of the user (e.g., the number of followers the user has) and the influence of the user-generated content (e.g., the number of likes on the user-generated content). The attribute of user popularity also varies from person to person. However, this approach is different from the user's social effort. Social effort depends on the user's own behavior and is an attribute that is actively acquired by the user, whereas user popularity is determined by the evaluation of other users and is an attribute that is passively given. Although users do not control their popularity on the platform, evaluations from other users can practically influence interactions between users (Chen and Lee, 2023; Yang et al., 2019). Users with higher popularity are more recognized in OPIC, which may attract more users to interact with them. Therefore, the following hypothesis is proposed:

H7: Users with higher levels of popularity are more likely to receive responses from other users in OPIC.

In social media, emotions have an impact on interactions between users (Xiong et al., 2020). Previous studies have explored the relationship between emotions and user interactions within different online communities. The conclusions of these studies are not consistent, probably due to differences in the research contexts. Some of these studies have suggested that content with positive and negative emotions is more appealing to users for discussion (Brady et al., 2017; X. Liu et al., 2020; Meire et al., 2016), while others have suggested that content with neutral emotions is more likely to receive responses from others (Yang et al., 2019). In OPIC, user-generated content such as posts and replies contains emotions. No study has yet revealed which emotions are more likely to influence interactions between users in OPIC; therefore, the following hypothesis is proposed:

H8a: Users with negative emotions are more likely to receive replies from other users in OPIC.

H8b: Users with positive emotions are more likely to receive replies from other users in OPIC.

H8c: Users with neutral emotions are more likely to receive replies from other users in OPIC.

Materials and methods

Data sources. To test the above hypotheses, this study collected and analyzed data from a well-known OPIC in China. Specifically, this study collected all posts and their corresponding replies in the cardiovascular section of the OPIC from March 2022 to March 2023, as well as attribute data on all users associated with these posts and replies. To ensure the integrity of the data, we excluded data such as users who logged out or set access rights and invalidated posts. A single communication between users may be episodic, which is insufficient to indicate close communication (Jiang et al., 2015). Therefore, this study dichotomizes the user interaction network (Krivitsky, 2012). We set the threshold of connection strength to 2, which means that only when users reply to the same user twice or more does this study take their connection into account in the user interaction network. This approach can better describe the interaction patterns between users. After filtering the data as described above, we ultimately obtained 1632 users. Taking these users as nodes and replies between two users as edges, the constructed user interaction network has 4535 directed edges.

Quantification of node attributes.

- Professional status

There are three user professional identities in OPIC: practicing physicians, medical students, and medical practitioners. Users must submit appropriate materials to authenticate professional status, such as a physician's license or medical student card, before posting and replying to posts in the OPIC. The certification mark of professional status will be awarded to the user only after the community administrator has reviewed and approved the certification materials. For the user attribute of professional status in OPIC, this study included 1 for practicing physicians, 2 for medical students, and 3 for medical practitioners.

- Community honorary status

Users can be granted honorary status if they meet certain requirements for the quantity and quality of their posts and replies in OPIC. In OPIC, users with a community honorary identity have a special honorary logo and enjoy privileges such as content promotion. In this study, users were assigned a value of 1 if they had any community honorary status and a value of 0 if they did not have community honorary status.

- IP affiliation

According to the allocation efficiency of health resources, different provinces in China can be categorized into three classes:

inefficient, weakly efficient, and effective (Sun and Luo, 2017). Among them, effective is the most efficient tier of health resource allocation, weakly effective is the second most efficient tier, and ineffective is the worst tier. We use Sun's findings to assign a value to the user's address attribute. This study assigns values of 1, 2, and 3 to provinces whose IPs are inefficient, weakly efficient, or effective at allocating health resources, respectively.

- Profile

The value of this user attribute is determined by whether the user has added content to their personal profile. 1 means that the user has added content to the profile, while 0 means that the user's profile is empty.

- Social effort

There are three main types of user-initiated social effort in OPIC: posting, reposting, and following. Among them, posting and reposting can directly establish social connections with other users, while following is an indirect way of socializing. In general, the more of these three behaviors a user has in an online community, the greater the user's socialization effort. This study uses the cumulative number of users who post, repost and follow to comprehensively measure users' social effort and classifies users into two categories: high and low social effort levels.

The specific process of data processing is described below. First, the data on the number of posts, the number of replies, and the number of concerns were observed to be nonnormally distributed, so the values were all log-transformed (considering that there are zeros in the data, the original data x are treated as ln $(x + 1)$). Second, the log-transformed user data were clustered using K-means, and the number of clusters was specified as two. The specific clustering results are shown in Table 1. By comparing the data of the final clustering centers of the two categories of users in Table 1, it is found that the data of one category of users are higher than those of the other category for all three indicators. The category of users with higher values is defined as "high social effort", while the other category is defined as "low social effort". In this study, the main purpose of clustering is to separate users with high and low social effort. To simplify the study, users were clustered into only two categories without a more granular division. K-means is a classic algorithm for solving clustering problems with the advantages of simplicity and speed and is appropriate for this study. The results of the analysis of variance (ANOVA) for the three clustering indicators are shown in Table 2. The results in Table 2 show that there is a significant difference between the two types of users in these three indicators, which also indicates that the K-means the clustering effect is good in this study from another perspective. Third, the clustering results in the second step were used to assign values to the two categories of users by assigning the 600 users with higher social effort as 1 and the other 1032 users with lower social effort as 0.

Table 1 Clustering results for "level of social effort" _ final clustering center.

	High social effort	Low social effort
(Logarithmically processed) Post volume	1.345	0.317
(Logarithmically processed) Repost volume	2.427	1.244
(Logarithmically processed) Attention volume	1.641	1.114

- Popularity

Some OPIC data can reflect the user's popularity: the number of posts viewed, liked, and collected, as well as the number of fans. These data are obtained passively by the user and depend on other users to generate them. The data processing of user popularity in this study are the same as those for social effort. We first took the logarithm of the number of followers, posts viewed, liked, and collected from each user. K-means was subsequently used for cluster analysis, and the final cluster center results are shown in Table 3. Table 4 shows the ANOVA results for each indicator of popularity, which indicate that there are significant differences between the two types of users in terms of these four indicators. According to the results of the above categorization, we assigned a value of 1 to the more popular 988 users and a value of 0 to the other 644 users.

- Emotion

This study used TextMind to assess the emotions of users in the OPIC. TextMind is a relatively established Chinese text analysis tool. With its built-in thesaurus, TextMind can count the frequency with which words related to psychological features are in user-generated texts to analyze the emotions expressed by users. Many studies have applied TextMind to sentiment analysis of Chinese texts (Sun and Luo, 2017; Yu et al., 2021; Zhang et al., 2022). This study uses TextMind to determine the frequency of positive emotion words and negative emotion words in each posting and replying text, respectively, to determine the corresponding user's emotional characteristics. Like Liu's study (X. Liu et al., 2020), the difference between the word frequencies of positive and negative emotion words in user-generated content is used to determine the user's emotion. By processing the data, we found that approximately 13% of users in OPIC used more negative emotion words than positive emotion words. These users were defined as users with negative emotions. The 13% of users with the highest degree of positivity (a greater difference in word frequency between positive and negative emotion words) were defined as positive emotion users. The rest of the users' emotions were not obvious enough and were defined as neutral emotional users.

Combined with the above quantification of each user attribute, the node attributes are presented in Table 5.

Exponential random graph model. ERGMs are relationship-based statistical models that can be used to explain how and why social network relationships emerge (Robins et al., 2007). The ERGM views the formation of social relationships as constructed from small local substructures. Patterns of local substructures are called configurations of networks and are subgraphs representing local regularities in the structure of a social network. The essence

Table 2 Cluster indicators for "level of social effort"_ANOVA.

	Clustering mean square	Mean square error	F value	*P* value
(Logarithmically processed) Post volume	401.178	0.222	1806.580	0.000***
(Logarithmically processed) Repost volume	531.150	0.257	2066.550	0.000***
(Logarithmically processed) Attention volume	105.418	0.229	461.161	0.000***

***$p < 0.001$

of the ERGM is to analyze the configurations of networks and ultimately study the formation of social structures.

Social life is full of randomness, social networks are not static, and the balance between randomness and orderliness has always been an important issue in social network research. The ERGM has both orderliness, i.e., configuration, and randomness added. In the context of the ERGM, if the configuration effect in the model is negligible, then the obtained network will be close to a purely random network. In addition, if the configuration effect is strong, then the obtained network will be highly structured. The ERGM combines randomness and orderliness, which makes it an important tool for social network research.

ERGM is a modified logistic regression that is able to infer the chance of occurrence of a particular configuration in the network and provides information related to statistical significance (van der Pol, 2019). By using the ERGM, it is possible to quantitatively analyze the trends of relationships in the network.

Table 3 Clustering results for "level of popularity " _final clustering center.

	High level of popularity	Low level of popularity
(Logarithmically processed) Number of fans	1.406	0.299
(Logarithmically processed) Number of post likes	2.056	0.966
(Logarithmically processed) Number of posts collected	1.590	0.107
(Logarithmically processed) Number of posts viewed	4.114	0.949

The general formula for the ERGM is as follows:

$$\Pr(Y=y)=\left(\frac{1}{k}\right)\exp\left\{\sum_{A}\eta_A g_A(y)\right\} \tag{1}$$

A in Formula (1) denotes the configuration in the network. η_A denotes the parameter corresponding to configuration A. $g_A(y)$ is a network statistic that takes the value of 1 if configuration A is observed in network y and 0 otherwise. k is a normalized quantity that ensures that the values in Formula (1) are within the normal probability (Robins et al., 2007).

Several types of network configurations are mentioned in the above assumptions, and a graphical representation of these assumptions translated into network configurations is shown in Appendix A.

Based on the above configurations, this study applies the ERGM and fits the coefficients of the model to the observed user interaction network data (Ghafouri and Khasteh, 2020). This study focuses on the results where the parameter estimates of the configuration are significantly positive, as this means that the probability of the configuration occurring in the observed network is greater than the probability of it occurring by chance (Liu and Liu, 2022; Robins et al., 2007).

Results and discussion

Results of hypothesis testing. The results of hypothesis testing using the ERGM are shown in Table 6. A positive and significant configured parameter estimate indicates that there is a corresponding trend in the interaction between users in OPIC (Robins et al., 2007).

Network structure effect. By analyzing the effect of network structure on user interaction in OPIC, this study focuses on reciprocity. H1 proposes that users in OPIC tend to interact

Table 4 Cluster indicators for "level of popularity " _ANOVA.

	Clustering mean square	Mean square error	F value	*P* value
(Logarithmically processed) Number of fans	477.498	0.570	837.986	0.000***
(Logarithmically processed) Number of post likes	463.092	0.670	690.784	0.000***
(Logarithmically processed) Number of posts collected	856.902	0.740	1158.685	0.000***
(Logarithmically processed) Number of posts viewed	3905.190	1.031	3786.958	0.000***

***$p < 0.001$

Table 5 Node attributes and their presentation.

Node attributes	Corresponding hypotheses	Type	Quantitative approach
professional_status	H2	Categorical variable	1 - Certified physicians 2 - Certified medical students 3 - Medical industry practitioners
honorary_status	H3	Binary categorical variable	1 - Have any community honor status 0 - Does not have any forum honor status
medical_ip	H4	Categorical variable	1 - Inefficient areas of health resource allocation 2 - Weakly efficient areas of health resource allocation 3 - Efficient areas of health resource allocation
profile	H5	Binary categorical variable	1 - Content edited in the personal profile 0 - Personal profile with empty content
effort	H6	Binary categorical variable	1 - High level of socialization effort 0 - Low level of socialization effort
popularity	H7	Binary categorical variable	1 - High level of popularity 0 - Low level of popularity
emotion	H8	Categorical variable	1 - Negative emotion 2 - Positive emotion 3 - Neutral emotion

Table 6 Results of hypothesis testing.

Configuration	Estimated value	Std. Error	P value
mutual	6.845	0.050	0.000***
professional_status	0.238	0.027	0.000***
honorary_status	0.551	0.046	0.000***
medical_ip	0.081	0.026	0.002**
profile	0.089	0.031	0.004**
effort	0.736	0.040	0.000***
popularity	0.056	0.043	0.192
emotion_negative	0.556	0.399	0.164
emotion_positive	0.515	0.400	0.198
emotion_neutral	0.904	0.398	0.023*

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

reciprocally with each other. The results in Table 6 show that the results for reciprocity were positive and significant ($\beta = 6.845$, $p < 0.001$), which suggests that reciprocal exchanges among users in OPIC are very common. Therefore, H1 is supported. In fact, many studies have identified reciprocal interactions between users in different online communities (X. Liu et al., 2020; Sun et al., 2022; Wu and Wu, 2021; Xiong et al., 2020). OPIC has the characteristics of a regular online community, gathering a group of physician users who share the same interests and goals (Chiu et al., 2006). These users are able and willing to use their expertize to collaborate with each other and resolve medical problems in OPIC (Yan and Davison, 2013).

Effect of user attributes. H2 ~ H7 discuss the impact of different node attributes on the formation of user interaction networks in OPIC.

H2 proposes that users with the same professional status are more likely to interact with each other. The results of this configuration in Table 6 are also positive and significant ($\beta = 0.238$, $p < 0.001$), and H2 is supported. This finding suggested that OPIC users tend to interact with users who share their professional status. That is, practicing physicians interact more with practicing physicians, medical students interact more with medical students, and medical practitioners interact more with medical practitioners. Professional identity may be an important factor for users in OPIC when interacting with others. Close communication with homogeneous users will reduce their loneliness (Hopp et al., 2022) and give them social pleasure. Users with the same professional identity have a smaller cognitive gap and may tend to communicate about common topics, which increases the likelihood of responding to each other. Therefore, users with the same professional status in OPIC tend to communicate with each other.

H3 proposes that the community honorary status of users in OPIC has an impact on the interaction between users. The corresponding parameter estimates in Table 6 are positive and significant ($\beta = 0.551$, $p < 0.001$). This finding suggested that users of the same community honorary status tend to interact with each other. That is, users with community honorary status are more likely to interact with each other; those without community honorary status are also more likely to interact with each other. H3 is also confirmed. This result suggested that users in OPIC also give attention to other users' community honorary status and tend to interact with users who share their honorary status.

H4 is associated with the location of the user, and the estimate of this parameter is also positive and significant ($\beta = 0.081$, $p < 0.01$). H4 is thus confirmed. This finding suggested that two OPIC users are more likely to interact if they are in provinces with similar health resource allocation efficiencies. A study by Deng et al. also revealed that geographic region affects interactions between physician users (Deng et al., 2023), but their findings are somewhat different from ours. Deng et al. performed their study from the perspective of knowledge transfer, using the GDP of each province as a criterion when categorizing regions. Their study noted that physicians in areas with higher GDPs had more medical expertize (Q. Q. B. Liu et al., 2020), ultimately concluding that physician users in economically developed regions tend to pass on their knowledge to users in poorer regions in OPIC. In contrast, our study focused on the homogeneity of medical conditions. This study suggested that regions with similar health resource allocation efficiencies may have similar health care constraints as physicians face in their work. These physician users are more likely to resonate and discuss the same medical issue with each other. Therefore, the result of our study is that users in areas with the same tier of health resource allocation efficiency are more likely to interact with each other in OPIC. These two studies differed in terms of their research perspectives and methods of categorizing regions, so the conclusions drawn in this study are not in direct conflict with those of that study.

H5 discusses the role of users editing their personal profiles. The results in Table 6 show that the estimate of this parameter is positive and significant ($\beta = 0.089$, $p < 0.01$). H5 is also supported. Although personal profiles provide nonmandatory information, the results of this study showed that users who edited their personal profiles were more likely to receive responses from other users in OPIC. Users who edit their personal profiles have a greater willingness to self-disclose, and it has been shown that self-disclosure has a direct positive impact on building intimacy (Bauminger et al., 2008; Park et al., 2011). Users who add a personal profile may be more likely to draw closer to other users, so these users are also more likely to receive responses from other users in OPIC.

H6 proposes that users with greater social effort are more likely to receive responses from other users in OPIC. According to the results of hypothesis testing ($\beta = 0.736$, $p < 0.001$) in Table 6, H6 is confirmed. The user attribute of social effort shows how much the user initiates social behaviors in OPIC. Social behaviors mainly include posting, replying, and following other users in the community. These social effort behaviors of users may reap the sympathy of other users (Tolonen et al., 2021), thus making it easier to receive replies from others in OPIC.

H7 proposes that users who are more popular in OPIC are more likely to receive responses from other users. The results of the estimates of this parameter in Table 6 are not significant ($\beta = 0.056$, $p = 0.192$). This result indicated that the number of occurrences of this configuration in the observed network was not significantly different from that in the randomized network. Moreover, this finding does not show that highly popular users tend to receive replies from other users in OPIC. H7 is rejected. This may be somewhat counterintuitive, but some studies indeed obtained similar results. For example, Wen et al. found that popular users of social media are weaker in terms of the speed and scale of information dissemination and are not as influential as intuitively thought (Wen et al., 2014). A study by Ruhela et al. also revealed that popular users were able to drive the popularity of topics on Twitter but did not increase the number of users who engaged with those topics (Ruhela et al., 2016).

Emotional effects of user-generated content. H8 considers the impact of the emotions of user-generated content on the interaction between users in OPIC. The results in Table 6 show that the parameter estimates of positive ($\beta = 0.515$, $p = 0.198$) and negative ($\beta = 0.556$, $p = 0.164$) emotions of the users are not insignificant, and both H8a and H8b are rejected. The parameter estimates of users' neutral emotions ($\beta = 0.904$, $p < 0.05$) were

Table 7 Robustness test results.

Configuration	M0		M1 (Remove "popularity")		M2 (10% of users in both positive and negative emotion)		M3 (8% of users in both positive and negative emotion)	
	Coefficient	*P* value	Coefficient	*P* value	Coefficient	*P* value	Coefficient	*P* value
mutual	6.845	0.000***	6.846	0.000***	6.846	0.000***	6.845	0.000***
professional_status	0.238	0.000***	0.236	0.000***	0.236	0.000***	0.235	0.000***
honorary_status	0.551	0.000***	0.546	0.000***	0.544	0.000***	0.548	0.000***
medical_ip	0.081	0.002**	0.084	0.001**	0.082	0.001**	0.085	0.001**
profile	0.089	0.004**	0.090	0.003**	0.086	0.005**	0.083	0.006**
effort	0.736	0.000***	0.766	0.000***	0.736	0.000***	0.743	0.000***
Popularity	0.056	0.192			0.049	0.249	0.047	0.271
emotion_negative	0.556	0.164	0.550	0.191	0.669	0.102	0.774	0.057
emotion_positive	0.515	0.198	0.514	0.221	0.553	0.177	0.456	0.263
emotion_neutral	0.904	0.023*	0.903	0.030*	0.836	0.040*	0.832	0.040*

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

positive and significant, and H8c was supported. The results of this study suggest that users with neutral emotions are more likely to receive responses from others. This finding is not the same as that of some previous studies (Brady et al., 2017; X. Liu et al., 2020; Meire et al., 2016), which may be due to the different community contexts involved. Users of OPIC are medical workers, and they may be relatively more inclined to talk about health care professional information rather than about emotional issues (Lu et al., 2017). Medical workers are responsible for saving lives, and every decision they make in their medical work can be a matter of patients' lives. These physician users spend very limited time communicating in OPIC and are more likely to communicate for medical information than for social entertainment. Neutral-emotion users specialize in outputting content that is objective and free of strong emotions and may be more likely to attract other users to interact with them.

Robustness test results. In this study, three models were constructed to test the robustness of the results. Model M1 removes the configuration "popularity" from the original Model (M0). M2 and M3 change the proportion of positive and negative users, respectively, based on M0. In M2 and M3, positive and negative users are defined in a similar way to the previous model. The top 10% and 8% of users who were assigned a negative sentiment score (difference in word frequency between negative and positive emotion words in user-generated content) were defined as negative users, respectively, and the same number of users were defined as positive users.

The results of the robustness tests of M1, M2 and M3 are shown in Table 7. After removing the "popularity" configuration, the results of M1 and M0 on the other configurations are the same. After the proportion of users with different emotions is changed, the results for M2 and M3 are also similar to those for M0. By comparing the results of the three test models with those of the original model, we found that the results of this study are robust.

Conclusion

This study examines the interaction patterns between users in OPIC. By collecting user interaction data and user attribute data from a well-known OPIC in China, this study established a user interaction network. Using the ERGM, we explore the emergence of configurations in the user interaction network and analyze the factors affecting user interactions in terms of network structure effects, node attribute effects, and emotion effects. Some reposting patterns among OPIC users were discovered. There is significant reciprocity in the OPIC of reposting interactions between users. Users with homogeneous characteristics in terms of professional status, community honor status, and geographic location were more likely to interact with each other. In addition, users who added a personal profile, had a higher level of social effort, and generated more neutral content were more likely to receive responses from others.

This study has several contributions to theory and practice.

In terms of theoretical contributions, this study applies the ERGM to OPIC and discovers new patterns of user interactions in OPIC, which enriches the related research. The literature on OPIC has mainly analyzed the characteristics of posts, whereas this study has focused on the interactive relationships between users. Moreover, this study identified several new user attributes in the OPIC context, such as professional status and social effort, which also affect the establishment of interactive relationships between users; however, the effects of these user attributes have not been mentioned in previous studies. This study addresses the question of how users interact with each other in OPIC, and some new conclusions are obtained in the OPIC context.

In terms of practical contributions, the findings of this study contribute to efficient communication among physician users and the development of OPICs. This study uses real data to reveal the impact of users' behaviors in OPIC, such as posting, replying, and editing their profiles, on their ability to build interactive relationships. These findings help suggest what changes users in OPIC should make to better communicate with others. For example, physician users can try to maintain neutral sentiments in generated content, increase social efforts, and edit content in their profiles. This study reveals the interaction patterns between users in OPIC, which can help administrators better understand the trends of user interactions on their platforms. Based on the findings of this study, community administrators can develop appropriate user recommendation mechanisms to facilitate long-term communication among users, thereby contributing to the prosperity of OPICs (Bock et al., 2005; Moghavvemi et al., 2017).

This study has several limitations. This study selected only the user interaction data from one period in the OPIC to test the hypotheses. However, we did not consider the dynamics of user interaction patterns over time. In addition, the data in this study came from cardiovascular departments, where additional physiologic medical issues were discussed among users; therefore, the findings of this study may not be applicable to OPICs, where additional psychological issues are discussed.

Data availability

The data analyzed and generated in the study are provided in the supplementary file.

Received: 20 September 2023; Accepted: 19 January 2024;
Published online: 01 February 2024

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Author contributions

Conceptualization, J.L. and Y.Z.; methodology, J.L. and Y.Z.; validation, Y.Z.; formal analysis, J.L. and Y.Z.; investigation, Y.Z.; resources, J.L. and Y.Z.; data curation, Y.Z.; writing—original draft preparation, Y.Z.; writing—review and editing, J.L. and Y.Z. All the authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethical Approval

Ethical approval was not needed, as the study did not involve human participants.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-024-02703-4.

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