


FULL-LENGTH RESEARCH ARTICLE

Technical Features of Asynchronous and Synchronous Community Platforms and their Effects on Community Cohesion: A Comparative Study of Forum-based and Chat-based Online Mental Health Communities

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Across online support communities, community cohesion varies by platform and can impact the self-disclosure of members and their exchanges of social support. Through a comparative study of forum and chat-based mental health communities, this research examines how technical features of both platforms influence community cohesion by affecting communication patterns among members, including evenness of communication, speed of communication, and number of participants. This study collected four weeks of data from 20 forum-based and 20 chat-based mental health communities in mainland China. Multilevel mediation analyses show that chat-based communities were more cohesive with higher member retention, network connectedness, and language conformity. Chat-based platforms facilitated faster communication and greater evenness of receiving messages among participants which in turn fostered community cohesion.

Lay Summary

Members of online mental health communities can benefit from more cohesive communities, where they are more likely to reveal themselves to each other and exchange social support. This article examines how technical features of forums and chat groups influence community cohesion by affecting patterns of social interactions among participants. Forums support asynchronous and threaded conversations while chat groups support synchronous and sequential ones. These technical features seem to affect how fast the communication is, whether the communication is evenly distributed, and how many members actively post messages that may contribute to community cohesion. Data from 20 forums and 20 chat groups on mental health in mainland China show that chat groups were more cohesive than forums. Members of chat groups in comparison

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to forums responded to each other more quickly and received each other's responses more equally, which partially accounted for greater community cohesion.

Keywords: online mental health community, community cohesion, chat group, forum, CMC

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Mental illness is a critical global issue which imposes a heavy burden on sufferers and society as a whole. According to recent evidence (Charlson et al., 2016), China alone accounted for 17% of the global mental health burden (i.e., 36 million Disability-adjusted life-years [DALYs] attributable to mental, neurological, and substance use disorders), while this number was 50 million for all developed countries combined. Moreover, the U.S. National Institute of Mental Health (2019) has estimated that 51.5 million adults in the United States live with a mental illness, and 44.8% of them have received treatment. However, out of over 100 million people suffering from a diagnosable mental disorder in China, more than 90% remain untreated (Charlson et al., 2016).

The gap between people needing care and those with access to care has led to an expansion of online mental health communities (OMHCs) in China that have served as prominent resources for peer-to-peer information, advice, and social support. Empirical studies have shown that engaging in OMHCs can help bring positive cognitive changes to those suffering from mental illness and reduce the likelihood of suicidal thoughts (De Choudhury & Kiciman, 2017; Pruksachatkun et al., 2019). OMHCs emphasize self-disclosure as people generally need to disclose personal information to seek and provide support, and to form mutual trust (Wang et al., 2015). In addition, self-disclosure can be therapeutic in its own right (Pennebaker & Chung, 2011).

In research examining small group and large-scale online communities, cohesion—which was defined as a community's tendency to stick together and remain united (Carron & Brawley, 2012)—has been identified as a key determinant of self-disclosure. People are more likely to reveal private information in online communities or groups with higher cohesion (Schwimmlein & Wodzicki, 2012; Stokes et al., 1983). Therefore, building community cohesion is fundamental for facilitating members' self-disclosure and further exchange of social support in OMHCs.

Individual-level interaction patterns serve as important precursors of community-level cohesion (Carron & Brawley, 2012), and the software infrastructure on which online communities are built can shape these social interaction patterns (Kraut et al., 2012; Preece et al., 2003). One of the most important technical features of online community software is whether it supports asynchronous modes of communication, such as forums, or synchronous modes of communication, such as chat systems (Hollingshead & Contractor, 2006). With regard to the organization of messages, another noteworthy technical dimension is whether the communication is organized around topics in threads or sequentially by time. To examine how the software infrastructure of an online community influences members' communication patterns and community cohesion, we propose an analytic framework (shown in Figure 1) to hypothesize theoretical links between technical features of forum-based and chat-based communities and three communication patterns among active participants (speed of communication; evenness of communication; and number of participants), that may impact community cohesion.

We tested these links using data from 20 forum-based and 20 chat-based OMHCs in mainland China. Results showed that communities using a chat-based platform were more cohesive than forum-based ones, as based on network density, reciprocity, text similarity, and language-style

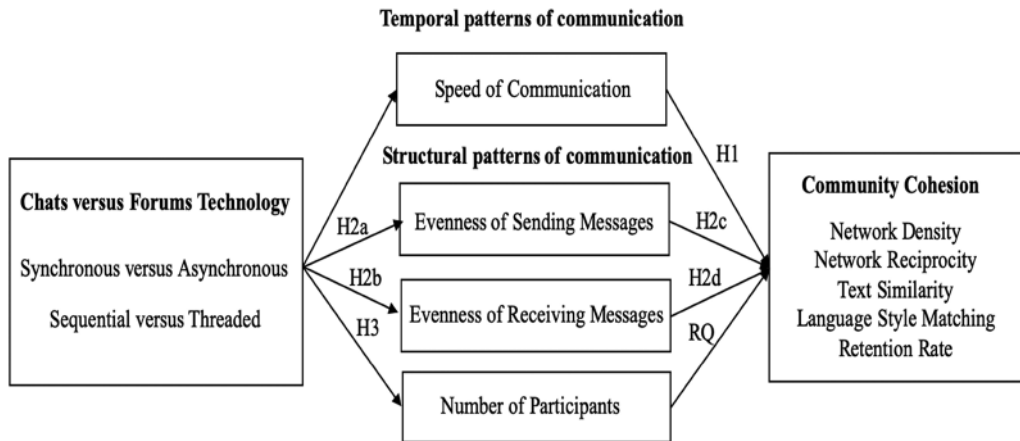


Figure 1. Analytic Framework and Hypotheses & RQ Development

matching among members, as well as higher retention of members. Multilevel mediation analyses suggested that differences in the evenness of receiving messages and the speed of communication partially accounted for the effects of platform type on community cohesion.

Analytic Framework and Hypotheses Development

Definition and Approaches to Community Cohesion

Cohesion is a longstanding research topic in group and community research, and has been considered central to group functioning and longevity (for a review, see [Dion, 2000](#)). Festinger and colleagues (1950) defined cohesion as “the total field of forces which act on members to remain in the group” (p. 37). This definition of cohesion still shapes the field and implies that cohesion is a multidimensional construct, though its components continue to be a source of debate and vary across different research contexts (e.g., [Carron & Brawley, 2012](#); [Dion, 2000](#)). Within this multidimensional framework, greater communication, higher uniformity of opinion and behavior among members, densely connected social networks and behavioral markers such as members’ commitment to the community are often used to indicate high cohesion ([Festinger et al., 1950](#); [Piper et al., 1983](#); [Moody & White, 2003](#)). In this study, we examined community cohesion through network connectedness, language conformity, and community commitment.

Because cohesion has been found to be associated with diverse desirable consequences (for a review, see [Beal et al., 2003](#)), extensive research has identified two conceptually distinctive mechanisms that underlie community cohesion—social identity and interpersonal bonds ([Prentice et al., 1994](#); [Ren et al., 2007](#); [Sassenberg, 2002](#)). While the social identity approach holds that cohesion is the result of shared identities, the interpersonal bond approach holds that cohesion forms when members develop a psychological attachment to one another ([Hogg & Turner, 1985](#); [Lott & Lott, 1965](#)). Thus, interpersonal interactions and other factors that cause members to like each other lead to their bond-based attachment to the community and higher cohesion overall. However, even though the social identity and interpersonal bond approaches are conceptually distinct, they are empirically related as factors such as interpersonal similarity lead both to identity-based attachment to a group and increased liking for its members ([Ren et al., 2007](#)).

Preece et al. (2003) defined online communities as a group of people who interact over time around a shared purpose, interest, or need in a virtual environment. The two distinct approaches to cohesion derived from small group studies have also been generalized to online communities, as members typically form identity-based or bond-based attachment to their communities (Kraut et al., 2012). Given our specific research focus on OMHCs and the shared social identity of mental illness sufferers, this study has taken an interpersonal bond approach to examine how technical features of forum-based and chat-based platforms influence community cohesion.

In their comprehensive review, Thye et al. (2014) concluded that bond-based cohesion was grounded in a "bottom-up" person-to-person interactions. Their work indicates the important role social interaction plays in creating and maintaining bond-based cohesion. In the following sections, we combine literature on asynchronous and synchronous computer-mediated communication (CMC) and online communities to hypothesize how technical differences between forum-based and chat-based communities affect active participants' social interactions, and therefore community cohesion.

Technical Features of Forum-based and Chat-based Communities

Two important technical features that distinguish modern online communities are whether the communication is asynchronous or synchronous and whether it is organized according to threaded topics or time-based sequences. Forum-based communities are typically supported by asynchronous communication systems in which members interact at different times, creating large time lags between messages and little expectation of sequential turn-taking in multi-person conversations. Chat-based communication, on the other hand, is more synchronous, characterized by close-to-real-time conversations and turn-takings. The temporal difference between forum-based and chat-based communities leads to differences in how messages are organized. Because of the often-large time lags between messages and lack of turn-takings, forum-based communities typically organize messages in the form of topic-based threads (Seo et al., 2009). A thread consists of a series of interrelated messages, starting with an initiating message that sets up the discussion topic followed by a sequence of reply messages generally responding to the initiating message. In chat-based communities, because people often take turns and respond to the most recent message sent to the community, messages are presented sequentially in the order in which they were produced rather than by topics.

Little research has examined how synchronicity of communication influences socio-emotional variables, such as community cohesion and substantially less research has investigated the differences between thread-based and sequentially organized communication independent of synchronicity. To fill these gaps, we propose our analytic framework in Figure 1 to investigate how technical features of forum-based and chat-based communities affect members' temporal and structural communication patterns and, subsequently, influence community cohesion. In particular, this framework asserts that the asynchronous versus synchronous nature of the technology and the ways messages are organized (threaded versus sequential) can influence the speed with which people communicate with each other, the number of people who actively participate, and how evenly they communicate with each other.

Speed of Communication and Community Cohesion

In their pioneering work, Short et al. (1976) argued that communication media vary in their ability to convey social presence—that is, they vary with regard to the degree to which one perceives the presence of the other person in the communication. Media richness theory (Daft & Lengel, 1986) drew on this notion of social presence to highlight immediate feedback as one important source of social presence and media richness. According to social presence and media richness theories, because chat-

based communities support faster communication than forum-based ones, they are likely to facilitate a higher sense of presence and intimacy among members (Walther & Tidwell, 1995). Given the premise that bond-based cohesion depends upon members' interpersonal attractiveness (Lott & Lott, 1965), we hypothesize that:

H1: Chat-based communities will be more cohesive than forum-based ones due to their faster communication.

Structural patterns of communication: Evenness of Communication

In the threaded presentation of messages in forum-based communities, topic discussion is typically organized around the initiating message, creating a "thread tree" (Shen et al., 2006). The tree-like structure of the thread makes the initiating message the center of attention, with replies stacked underneath. Threading allows members to identify the topics that interest them and decide what to read by glancing at the subject line or initial text of the initiating messages in a list of threads. However, threading disrupts the linear flow of conversations (Hollingshead et al., 1993). That is, threads are generally independent of each other and do not need to be read in a specific order to be understood. Likewise, because most messages in the threads are replies to the initiating messages, the replies do not have to be read in the order in which they were written.

Chat-based communities, on the other hand, normally display messages in the chronological order in which they were produced, with messages scrolling off the screen as they were pushed up by more recent ones (Donath et al., 1999). This design choice means that people are supposed to focus on and reply to the message posted by the participant who spoke last, making the initiating messages less salient. When reading the temporal stream of messages, the "reply-to" relations among communicators are implicit and must be inferred based on both the proximity of messages in the stream and their contents. Since messages are presented sequentially, messages on different topics can be heavily interwoven, making it difficult to identify the messages that belong to the same topic at a glance (see Figure A1 in Supplementary Appendix A for sample conversations).

In online communities, conversations can be conceptualized as communication networks composed of active participants and their reply-based relations (Himmelboim, 2008). One of the most important structural properties of a social network is the extent to which the network is or is not centralized, which can be gauged by the distribution of degree centrality in the network (Bonacich, 1987). Decentralized networks by definition entail more even communication among participants than a more centralized network in which the center of the network is often the principal source and target of communication (Moody & White, 2003).

Because the threaded display of messages in forum-based communities focuses attention on the initiating message, it is likely to result in more centralized communication networks and conversely less even communication among participants. The sequential display of messages in chat-based communities which highlights the last message produced should flatten the communication structure and equalize social interactions. Given that decentralized networks entail more even participation and given that communication in online communities is a bidirectional process involving both sending and receiving messages, we propose the following hypotheses:

H2: Chat-based communities will show (a) higher evenness of sending messages and (b) higher evenness of receiving messages among participants.

Evenness of Communication and Community Cohesion

As Himelboim (2008) noted, when communication is more evenly distributed in online communities, members are more likely to give and receive the information that they need from others and, in the context of OMHCs, evenness of communication shapes how members exchange social support. According to Lawler and Yoon's (1996) relational cohesion theory, members' attraction to one another is a result of their repeated communication. For dyadic attraction to influence community-level cohesion, people must be able to interact with many other community members (Thye et al., 2014). This suggests that OMHCs with more even communication should be cohesive as most participants can interact with most others. Considering that communication entails both sending and receiving messages, we assume that:

H2: Chat-based communities will be more cohesive than forum-based ones due to their higher (c)evenness of sending messages and (d) evenness of receiving messages.

Structural Patterns of Communication: Number of Participants

The asynchronous, threaded nature of communication in forum-based communities and the synchronous, sequential nature of communication in chat-based ones can influence the number of members who actively participate in either community. The asynchronicity of forum-based communities means that people don't need to be simultaneously present to participate, and the well-structured threads make it easier for members to review prior messages and respond at their convenience. In this way, forum-based communities support participation by virtually any number of people at any time. In synchronous chat-based communities, however, the absence of explicit "reply-to" relations and their sequential nature implies that members generally need to be present to keep track of an ongoing conversation and respond immediately before the topic shifts. The need for co-presence and immediacy makes it difficult for people to remain engaged in the conversations whenever a new message appears and may thus hinder active participation.

Perhaps because the asynchronous communication and the threaded display of messages in forum-based communities makes it so much easier to keep track of discussions, they generally do not set caps on membership. Since information overload is more of a problem in chat-based communities, they often have a membership cap. For example, a *WhatsApp Group* can only hold 256 members and a *WeChat Group* allows for, at most, 500. Additionally, many chat-based communities require administrators to initiate or approve new memberships, complicating the process of joining (Kraut & Fiore, 2014). In summary, forum-based communities should facilitate more active participants than chat-based ones due to their technical differences.

H3: Forum-based communities will have more active participants than chat-based ones.

Number of Participants and Community Cohesion

Moreland and Levine (2001) argued that members' commitment to a group depends on how well it meets their needs and provides the resources they desire. As a minimum requirement, OMHCs must have a large enough and varied enough membership to provide adequate and versatile support for their members. However, more active participants do not necessarily lead to greater community cohesion, since people tend to prefer smaller online communities to larger ones (Kraut et al., 2020). As the number of active participants and the amount of communication increase, members may feel

overwhelmed as the “message traffic” exceeds their ability to easily respond, which can drive them away from the community (Jones et al., 2004) and undermine cohesion. As the number of participants in a community can have opposing effects on cohesion, we ask: *RQ: How will the number of participants influence community cohesion?*

Data and Method

Data Collection and Sampling

By searching for the terms *depression*, *anxiety disorder*, *bipolar disorder*, *eating disorder*, and *personality disorder* in Chinese, we identified over 300 OMHCs hosted on the forum-based communities *Baidu Tieba* (百度贴吧) and *Douban Group* (豆瓣小组), and the chat-based communities *WeChat* and *QQ*. We randomly selected 10 communities that contained at least 10 conversations that members had initiated during December, 2019 from each of the four platforms (see [Table A1](#) in [Supplementary Appendix A](#) for a list of the sampled communities and information about the four platforms). Four weeks of data were collected from each community.

We wrote a Python-based web scraper (available at <https://codeocean.com/capsule/1539709/tree>) to collect all publicly accessible conversations that started in December 2019 in 20 forum-based communities. To collect data from chat-based communities, the first author joined the selected communities through publicly advertised community QR codes and downloaded data that were available to all community members. Although membership needed to be approved by a community administrator, membership was open to all and the application did not ask for reasons for joining or for any other personal information. None of the communities had policies restricting academic research.

All conversations started in December 2019 were collected from *WeChat* communities. Because some of the *QQ* communities we initially sampled had fewer than 10 active conversations, we dropped them and collected data from *QQ* communities from December 15, 2019 through January 15, 2020. The entire dataset included 4,423 conversations comprising 30,787 messages from 20 forum-based communities and 7,561 conversations with 169,680 messages from 20 chat-based communities. In total, 9,262 unique active participants were included.

During data collection, members of the research team only observed and did not post in the communities or contact any members to avoid external influence on the communities. Given the public nature of the selected online communities and deidentification of data before analysis, the Institutional Review Board (IRB) at Carnegie Mellon University classified this data collection as non-human subjects research under U.S. federal regulations.

It should be noted that, though many chat communities on *WeChat* and *QQ* are oriented towards communication within offline social networks, this occurs much less frequently for topical and identity communities, which were two attributes of the mental health communities we studied here (Kraut et al, 2020). We therefore expect the effect of prior acquaintanceships on chat-based communities to be minimal and the results should not be affected by it.

Identifying conversations

Conversations are much more difficult to identify in chat-based communities than in forum-based ones for researchers as well as for members. Contrary to forum-based communities which are characterized by conversation threads, messages in chat-based communities are displayed linearly by posting time. “Reply-to” relations are implicit, topics of conversations can drift and messages on different topics are often intertwined. Thus, conversations must be inferred from message content and

Table 1. Descriptive Statistics and Correlations

Variable	Descriptive statistics						Correlations					
	Forum			Chat			Chat	Lag	Sending	Receiving	Participants	Cohesion
	Mean	S.D.	Mdn	Mean	S.D.	Mdn						
Response Lag	4154.5	3213.2	3545	49.56	80.04	32.77	-0.67	1.00				
Evenness of Sending	0.7	0.06	0.71	0.63	0.03	0.63	-0.58	0.43	1.00			
Evenness of Receiving	0.42	0.07	0.42	0.55	0.04	0.56	0.75	-0.48	-0.31	1.00		
Number of Participants	84.99	107.05	52.5	84.14	48.17	74	-0.01	-0.25	-0.03	-0.14	1.00	
Cohesion	0.27	0.06	0.27	0.46	0.07	0.46	0.82	-0.57	-0.46	0.73	-0.02	1.00

Notes: N = 80 community-weeks for forum-based and chat-based communities. To make interpretation easier, the number of participants and the response lag are expressed in original units, before log transformations. Response lag is expressed in minutes.

contextual information such as timing and usernames. To extract coherent topic-based conversations from message streams and to detect the implicit "reply-to" relations in the messages, we recruited and trained four Chinese students from a research-based university to manually code the data from the 20 chat-based communities by grouping messages into topic-based conversations and identifying the addressee for each message.

In the *conversation identification task*, coders were instructed to disentangle the temporally ordered messages and to group topically related messages posted within 12 hours of each other into separate topic-based conversations. In the *addressee identification task*, coders annotated the addressee of each message (i.e., the username of the person intended to receive the message) to clarify the "reply-to" relations. Intercoder reliability was high, with the average *Cohen's Kappa* (1960), which represents agreement corrected for chance, being .86 for *conversation detection task* and .93 for *address identification task*. The remaining messages were then coded separately by single coder (see [Supplementary Appendix B](#) for coding scheme and measures of intercoder reliability).

Measures

Independent Variable: Platform Type

The *Chat* dummy variable indicates whether the community was hosted on a synchronous chat-based platform (coded as 1) or an asynchronous forum-based one (coded as 0).

Dependent Variable: Community Cohesion

Community cohesion was a composite variable measured by averaging two measures of network connectedness (*network density*, *network reciprocity*), two measures of language conformity (*text similarity*, *language style matching*), and a measure of community commitment (*retention rate*), with the unit of analysis being the community-week. The resultant community cohesion ranged from 0 to 1, with scores closer to 1 reflecting higher cohesion. The Cronbach's alpha for the five components of cohesion was 0.86, indicating strong internal consistency.

Prior research has shown that cohesive groups tend to demonstrate higher network connectedness, as based on observable direct ties among members (Markovsky & Lawler, 1994; Moody & White, 2003). To operationalize network connectedness, we used *network density* to measure overall network connectedness, and *network reciprocity* to measure the extent to which pairs of communicators are reciprocally linked (Granovetter, 1973). Because of the substantial turnover of members participating in the online communities, our unit of analysis was the community-week. In each community, conversations that took place over the course of a week constructed a communication network for analysis. *Network density* is defined as the number of actual reply links divided by the number of all possible reply links, based on the number of active participants. *Network reciprocity* refers to the percentage of dyads who replied at least once to each other. To focus on interpersonal contacts, the sample dropped self-loops when participants replied to themselves. Both *network density* and *network reciprocity* ranged from 0 to 1, with scores closer to 1 reflecting higher network connectedness. We calculated these metrics using the *igraph* package in R 3.6.3 (R in the following) (see [Supplementary Appendix C](#) for examples).

Language conformity is another well-validated indicator of community cohesion. A recent study of mental health support groups (Sharma & Choudhury, 2018), for example, showed that linguistic conformity was positively associated with social approval and acceptance among members, a symbol of cohesion. Similarly, conformity in the use of function words in both offline and online communities can reliably

signify community cohesion (Gonzales et al., 2010). Based on this prior work, we used *text similarity* and *language style matching* as measures of language conformity (McPherson et al., 2001; Gonzales et al., 2010; see [Supplementary Appendix D](#) for examples). To calculate *text similarity*, we employed *JiebaR* and *text2vec* packages in *R* for word tokenization and vectorization. We calculated the cosine similarity between each active participant and all remaining active participants posting a message in the same week; these individual-level scores were then averaged to yield community-level *text similarity*, which ranged from 0 to 1 with scores closer to 1 reflecting higher language conformity.

Language-style matching (LSM) measures the degree to which active participants use function words in a similar way. The simplified Chinese LIWC 2015 (Linguistic Inquiry and Word Count), validated in prior research (Huang et al., 2012), was used as a means of capturing the degree to which people use function words in their messages. The formula developed by Gonzales et al. (2010) was then adapted to calculate the degree of *LSM* between each active participant and the remaining active participants in the week. Eight categories of function words were included: auxiliary verbs, common adverbs, personal pronouns, indefinite pronouns, prepositions, negation terms, conjunctions, and quantifiers. Individual-level scores of *LSM* were averaged to yield community-level *LSM*, which ranged from 0 to 1 with scores closer to 1 reflecting higher language conformity.

Community commitment, which reflects members' willingness to stay in a community and contribute to it (Ren et al., 2007), has also long been linked to community cohesion. In Lawler and Yoon's (1996) relational cohesion model, specific commitment behaviors such as gift-giving, staying, and contributing were treated as behavioral indicators of cohesion. Across various types of online communities, members' commitment to their communities was robustly related to community cohesion (e.g., Kraut et al., 2012; McPherson et al., 2001).

We used *retention rate* to measure community commitment (Panek et al., 2018). In each community, the retention rate refers to the percentage of members who posted a message in week $N-1$ and returned to post in week N . Community-level *retention rates* ranged from 0 to 1, with rates closer to 1 reflecting higher community commitment. Since we collected only four weeks of data, we can only calculate the *retention rate* for weeks 2, 3, and 4 and averaged them.

Mediating Variables

Speed of Communication

Speed of communication in a conversation was measured as the inverse of the response lag in minutes between an initiating message and its first reply, and the average lag between the initiating message and all replies. We averaged conversation-level response lag measured in the same week to get community-level response lags. Because this metric had a long-tailed distribution, we used log transformed *speed* in the analysis.

Evenness of Communication

We measured the *evenness of sending messages* and *evenness of receiving messages* separately, using the *igraph* package in *R* to calculate the out-degree score (i.e., the number of messages sent) and in-degree score (i.e., the number of messages received) for each active participant in a conversation. We then calculated the Gini coefficient of the conversation, a widely used measure of unevenness of a distribution (Lambert & Aronson, 1993), using the *R ineq* package. We took one minus the average conversation-level Gini coefficients from the same week to generate a community-level measure of evenness of communication. Low *evenness of sending messages* means that few participants posted a

large and disproportional number of messages during the week; low *evenness of receiving messages* means that only a few participants were "paid attention to" and highly replied during the week; while a high evenness of sending or receiving messages means that many participants were posting messages or receiving replies respectively. The evenness scores ranged between 0 and 1.

Number of Participants

Number of participants is measured by the number of unique participants who posted at least one message in the given week. Because this metric had a long-tailed distribution, we used the log transformed *number* in the analysis.

Data Analysis

Multilevel mediation regression was applied to test whether evenness of communication, speed of communication and number of participants (as mediating variables) account for the differences in community cohesion between forum-based and chat-based communities. Due to the nested nature of the data, with the unit of analysis being a week of data nested within a community, we conducted multilevel mediation analyses using Structural Equation Modeling (SEM), implemented with the Stata 14 *gsem* package. The model simultaneously examines: (a) the effects of platform type (forum-based versus chat-based) on community cohesion; (b) the effects of platform type on the potential mediators (speed of communication, evenness of communication and number of participants); and (c) the indirect effects of platform type on community cohesion via mediators (MacKinnon, 2008).

Results

Table 1 shows the descriptive statistics of the potential mediators and community cohesion by platform type as well as their correlations.

Before conducting multilevel mediation analyses, we built a null model to test whether multilevel analyses were needed. The intraclass correlation coefficient (ICC) of 0.83 indicates that 83% of the week-to-week variance in community cohesion can be attributed to the community, supporting the use of multilevel modeling.

Results from the multilevel mediation model (all mediators in one model) are shown in Table 2 and summarized in Figure 2. As expected, chat-based communities had faster communication ($b = 1.822$, $SE = 0.108$, $p < .001$) and more even receipt of messages ($b = 1.494$, $SE = 0.105$, $p < .001$). However, contrary to expectations, forum-based communities had more even sending of messages ($b = -1.155$, $SE = 0.132$, $p < .001$). Forum-based and chat-based communities did not differ significantly in their number of active participants ($b = 0.329$, $SE = 0.284$, $p = .246$).

In addition, the results indicate that chat-based communities were more cohesive than forum-based ones ($b = 1.631$, $SE = 0.093$, $p < .001$). Of the total effects of platform type on cohesion, 65% was mediated by the communication patterns (1.056/1.631) and 35% was direct (.574/1.631). A closer look at the nature of the mediation reveals that the positive association between chat-based community and community cohesion was partially mediated by the speed of communication ($b = 0.646$, $SE = 0.245$, $p < .01$) and the evenness of receiving messages ($b = 0.395$, $SE = 0.105$, $p < .001$), but not by evenness of sending messages ($b = 0.026$, $SE = 0.061$, $p = .673$) nor by the number of participants ($b = -0.010$, $SE = 0.020$, $p = .615$). This is because evenness of sending messages and the number of participants were not themselves associated with cohesion. As a robustness test (see Table A2 in

Table 2. Multilevel Mediation Analysis Results from a Structural Equation Model

DV	IV	Path	Coef.	S. E.	z	P > z
Cohesion	Chat	Total effect	1.631	0.093	17.460	0.000
Cohesion	Chat	Direct effect	0.574	0.255	2.250	0.024
Cohesion	Chat	Total indirect effect (all mediators)	1.056	0.245	4.320	0.000
Cohesion	Chat	Indirect effect through Speed	0.646	0.245	2.640	0.008
Cohesion	Chat	Indirect effect through Sending	0.026	0.061	0.420	0.673
Cohesion	Chat	Indirect effect through Receiving	0.395	0.105	3.770	0.000
Cohesion	Chat	Indirect effect through Participants	-0.010	0.020	-0.500	0.615
Cohesion	Speed	Direct effect	0.354	0.133	2.670	0.008
Cohesion	Sending	Direct effect	-0.022	0.053	-0.420	0.672
Cohesion	Receiving	Direct effect	0.264	0.068	3.910	0.000
Cohesion	Participants	Direct effect	-0.031	0.055	-0.560	0.577
Speed	Chat	Direct effect	1.822	0.108	16.890	0.000
Sending	Chat	Direct effect	-1.155	0.132	-8.760	0.000
Receiving	Chat	Direct effect	1.494	0.105	14.280	0.000
Participants	Chat	Direct effect	0.329	0.284	1.160	0.246

Notes: All continuous variables were standardized before analysis. Chat is a binary variable, where 1 = a chat-based community and 0 = a forum-based community. Speed=Speed of Communication, Sending = Evenness of Sending Messages, Receiving = Evenness of Receiving Messages, Participants = Number of Participants.

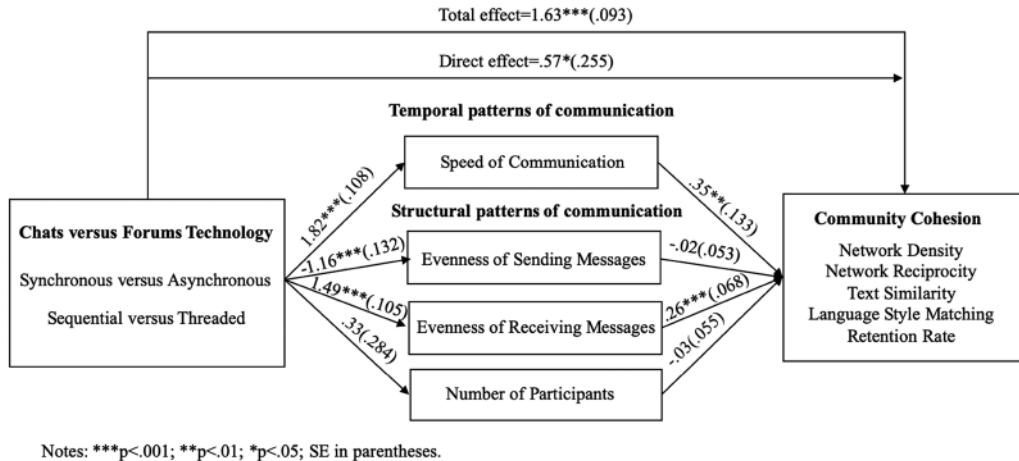


Figure 2. Summary of Multilevel Mediation Analysis

Supplementary Appendix A), the results from four single-mediator models were consistent with the multiple-mediators model. Despite the high correlations between some of the mediators (the average absolute correlation among mediators was 0.273; see Table 1), with VIF scores below 4, multicollinearity was not an issue.

Discussion

In the present study, we compared the community-level cohesion and individual-level communication patterns among participants in forum-based and chat-based OMHCs. Results show that chat-based communities were more cohesive than forum-based ones, and this difference was partially mediated by the faster communication and greater evenness of receiving messages in chat-based communities. These results are consistent with the thesis that technical features of the community platforms—whether they support synchronous or asynchronous communication and whether they have a sequential or threaded organization of messages—influence community cohesion by affecting communication patterns.

Community cohesion is crucial to the vitality of the community as well as to members' willingness to reveal themselves and exchange support with each other. This study empirically identifies and examines the antecedents of bond-based cohesion in the context of online support communities. Consistent with relational cohesion theory (Lawler & Yoon, 1996), social interaction plays an important role in influencing the interpersonal bonds between community members. We also demonstrate that speed and evenness of communication are equally important to communication frequency in influencing community cohesion. For a better understanding of the social aspects of an online community, such as community cohesion, it is necessary to look closely at the communication patterns enabled or constrained by the technology.

When it comes to specific communication patterns, the evenness of receiving messages among members was predictive of community cohesion. In online communities, people can exchange social support and cultivate long-term supportive relationships by getting replies. Though prior research (e.

g., Himelboim, 2008) has found that large-scale online interactions tend to follow a power-law distribution wherein most participants receive fewer messages and a few participants receive the most, this study suggests that ways of organizing conversations may contribute to the equalization of distribution in receiving replies among participants. Since evenness of sending messages was not related to cohesion, the results suggest that it made little difference, whether messages came from a few core contributors or from a broader cross-section of the community.

Speed of communication was also essential to a cohesive online community. Despite the importance of time in CMC, previous research has been limited to task-oriented groups that emphasize performance (e.g., Lew et al., 2018). We observed in this study that quick responses entail important relational implications in real-world social-oriented online communities. Additionally, mental health support communities are often characterized by members' urgent needs for social support and companionship, quick responses may thus ease their stress in times of uncertainty. Therefore, the appropriate design choices for online communities depend on how well the design aligns with the purpose of the community and the social needs of its members.

Contrary to our hypotheses, forum-based communities showed a higher evenness of sending messages than chat-based ones. One possible explanation is that forum-based communities have more one-time posters. Specifically, the evenness of sending messages would be inflated if most participants of a community posted only once. A follow-up analysis confirmed this explanation; the proportion of one-time posters was much higher in forum-based communities (79%) than in chat-based ones (47%). Future research into the causes and consequences of these one-time posters in online communities is needed. Another noteworthy finding is that evenness of sending messages was negatively correlated with evenness of receiving messages (-0.31). This is consistent with what Himelboim (2008) suggested "the more you give does not always result in the more you get." In online communities, posting messages may be more of a self-motivated activity, whereas getting a reply may be a function of the technical features of the community as well as the group interaction process, such as preferential attachment (Newman, 2001).

Although forum-based communities had more registered members than chat-based ones, they did not have more active participants. Instead, forum-based communities may consist of more lurkers or people who have left the community without deregistering from it (Chidambaram & Tung, 2005). The number of active participants was not a significant predictor of community cohesion either. In light of the "size paradox" found in prior research (e.g., Himelboim, 2008), it is possible that communication overload in large communities may override the potential benefits of having more support resources available. Future studies may test this "size paradox" in experimental environments to identify the underlying mechanisms.

Implications and Limitations

Theoretical Contributions of the Study

This work contributes to the current knowledge of bond-based cohesion, computer-mediated communication, and the socio-technical nature of online communities. Unlike prior research, which has focused on social factors such as governance structures, norms and rules, and roles people play in their communities, this study has uncovered that both social and higher-level technical design choices can influence the social features of an online community, including elements of cohesion like retention rates.

Specifically, as a consequence of the synchronicity of chat-based communities, members can communicate faster and thus form tighter connections. It suggests that timely feedback plays a vital role in fostering attachment between members. There are two possible explanations: on one hand, speed in CMC functions as a focal nonverbal cue that signals communicator's presence and increases interpersonal intimacy (e.g. [Walther & Tidwell, 1995](#)), which adds a relational dimension to the communication; On the other hand, in OMHCs where members are in strong need of nurturing support, a real-time, interactive conversation allows for more spontaneous communication and timely provision of help that meets their immediate and situational needs.

Evenness of receiving messages facilitated by the sequence-based organization of messages in chat-based communities provides each member of the community with equal opportunities to receive the information and care from their fellow members, which are crucial factors in the establishment of supportive relationships. Interestingly, we also found that the evenness of sending messages and the number of participants were not associated with bond-based cohesion, suggesting that, when it comes to fostering interpersonal bonds in an online support community, knowing more members is less important than knowing members intimately (faster communication) or getting "answered" by others (evenness of receiving messages). Thus, members' attachment to their community can be enhanced when other members promptly react or respond to them, even if the replies come from only a small segment of the membership. This finding echoes the theory of "Cyberostracism" ([Williams et al., 2000](#)), that being ignored online can lead to a lost sense of belonging to a group. While the number of contributors is important in increasing the amount of and diversity of information, it may be outweighed by information redundancy or, at the very least, it may not be essential for making a community cohesive.

This study also makes methodological contributions. We identified and incorporated five validated indicators that effectively measured community cohesion in an objective and robust manner. These metrics capture complementary dimensions that reflect granular changes in community cohesion. Moreover, rather than conducting a case study within a single online community as much research does, we examined the linkages between technical features, communication patterns, and community cohesion across forty different online communities.

Implications for Online Community Design

This study suggests important practical implications for fostering cohesion in OMHCs through technical design choices. Since community cohesion may be enhanced by the evenness of receiving messages, the software systems that organize and visualize conversations on community interfaces could be designed to maximize each participant's chances of receiving a reply. For example, messages in forum threads can be presented to increase the visibility of non-thread initiators so that those people are more likely to get responses from the community. Moreover, our findings suggest that faster communication contributes to cohesion. Even though forum-based communities are characterized by asynchronous communication, community designers can also enable chat features within forums. For example, *Facebook* launched *Chats* in its *Groups* product that allows members to engage in real-time conversations. This can be especially valuable in health-related contexts or disasters where quick actions are emphasized.

Limitations of the study

The present study was restricted by several limitations. First, and perhaps most importantly, this study was correlational and neither longitudinal methods nor random-assignment experiments were used to test the causality between platform type, communication patterns, and community cohesion.

Second, despite the highly reliable suite of behavioral metrics we used to measure cohesion, we lacked self-report measures of members' attachment to the community or perceived cohesion. Moreover, as a result of selecting Chinese research sites and a four-week time span for convenience, our findings were limited in terms of generalizability and in terms of longer-term observations of community dynamics. Future research would benefit from performing sensitivity analyses to test our findings across different time frames and cultures.

We considered only three aspects of social interactions, including speed of communication, evenness of communication, and number of participants. Our model could be refined by adding other aspects of social interactions or individual factors such as gender, membership tenure, and roles. Further, the automated text analysis techniques we used introduced potential bias and inaccuracy, but allowed us to examine a large number of communities and social interactions. A mixed-method approach may be used in the future to overcome these limitations. We restricted our research sites to OMHCs, despite the importance of the communities in their own right, future researchers are encouraged to test our hypotheses in other types of online communities.

In addition, even though community cohesion generally has a variety of beneficial effects on members and communities at large, more research is needed to examine the downstream effects of community cohesion, including their unintended consequences. For example, a tightly-knit community may result in the exclusion and prejudice of out-group members, as well as a redundancy of information which may be detrimental to the community (Kraut et al., 2012).

Conclusion

This study is a preliminary investigation of how the technical features of online community platforms are associated with social interaction processes and community cohesion. As communication technologies evolve and new forms of online communities emerge, the technical structures that characterize online communities should be considered in understanding the social dynamics within them. It is important for researchers, community designers, and managers to recognize the impacts of software designs on online communities as well as how well the software matches community needs.

Data Availability

The data underlying this article cannot be shared publicly for the privacy of online community members and ethical consideration. The data could be shared on reasonable request to the corresponding author.

Supporting Information

Additional Supporting Information is available in the online version of this article. Please note: Oxford University Press is not responsible for the content or functionality of any [supplementary materials](#) supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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Conflict of Interest

The authors do not have conflict of interest to disclose.

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