Measuring the Users and Conversations of a Vibrant Online Emotional Support System

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***Abstract*—Online social systems have emerged as a popular medium for people in society to communicate with each other. Among the most important reasons why people communicate is to share emotional problems, but most online social systems are uncomfortable or unsafe spaces for this purpose. This has led to the rise of *online emotional support systems*, where users needing to speak to someone can anonymously connect to a crowd of trained listeners for a one-on-one conversation. To better understand who, how, and when users utilize emotional support systems, this paper examines user and conversation characteristics on *7 Cups of Tea*. 7 Cups of Tea is a massive, vibrant emotional support system with a community of listeners ready to help those with any number of emotional issues. Intriguing insights, including evidence of world-wide adoption of the service, the need to seek immediate support from many others, and a rich-get-richer phenomenon underscore a growing need for online emotional support systems and highlight important aspects to promote their long-term viability.**

Keywords: Online social networks; emotional support systems; user behavior; statistical analysis; network evolution.

I. Introduction and Motivation

When people face with an emotional problem, it is often their friends, colleagues, and family to whom they turn to seek relief [1]. However, it is intuitive that online social systems (e.g. social networks or social media) are not an ideal modality to share emotional problems with others. This is because many online social systems: (i) only enable "semi-private" communication, with messages exposed to many others; (ii) save conversations forever; and (iii) cause a tension for users to express their true-self while displaying an idealistic impression of themselves on others [2].

As online social systems grow to become the dominant mode of communication for society's youngest generations [3], there is a need for them to be built specifically for the purpose of sharing emotional problems in an anonymous and safe way. This need is already being realized through *online emotional support systems*, which are typically built on top of message boards or anonymous chat rooms. Modern emotional support systems assist cancer patients and victims [4], [5], [6], those contemplating suicide[1], and those facing a major medical prognosis [7]. While these systems are very useful for those facing a specific, critical problem, they are not meant to handle users who face any kind of emotional problem, including minor cases "of the blues" or a "bad day". For more general emotional support, the largest and leading online social system people turn to is *7 Cups of Tea*[2] (7cot). 7cot facilitates connections between a crowd of live "listeners", who are users trained to support people facing a variety of emotional problems, and other users needing support. In the twenty months since its inception in December, 2013, 7cot has attracted more than 90,000 listeners who have helped over 1.4M people in over 3 million one-on-one *conversations* (private asynchronous or real-time message exchanges). Its tremendous popularity demonstrates a demand for safe online spaces providing emotional support.

Our previous work [8] investigated the mechanisms by which members choose to connect to specific listeners, and what design choices (e.g., gamification mechanisms such as "points" and "badges") and user behaviors (e.g., login and conversation frequencies, forum use) encourage long term engagement on the platform. In this paper, we turn our attention to understanding the people who form the community of 7cot users and the characteristics of the conversations they hold. Insights from our user-centric analysis explain the typical patterns of users, the aspects of the system important to them, and thus, the qualities an emotional support system exhibits if it is to become viable over a long period of time.

The layout of this paper is as follows: Section II reviews the related work on understanding the users of online support systems. Section III gives an overview of the 7cot platform. Section IV presents our analysis of users and conversations. The paper concludes with a summary of our findings and directions for future work in Section V.

II. Related Research

A small number of works have tried to understand the users and their behaviors on online emotional support systems. Maloney-Krichmar *et al.* investigated the dynamics of group interactions among an online self-help group for knee injuries [9]. Barak *et al.* established a positive relationship between the amount of activity of adolescents in an online

[1] http://www.crisischat.org, http://befrienders.org

[2] http://www.7cupsoftea.com

support group and the emotional relief they felt [10], underscoring the importance of building online systems that facilitate user interactions. Ploderer *et al.* delved into the discussion topics on a Facebook group of people trying to quit smoking, and found that most supportive responses come from those who just began trying to quit, rather than long-term quitters [11]. Recently, mobile crowd sensing technology has been exploited in the frameworks of experimental social psychology and mental health care to infer people emotions and predict behaviors, such as depression or social isolation [12], [13], [14].

This paper differentiates itself from these efforts in multiple ways. First, emotional support systems studied in the past were built using message boards or an existing feature of a social network platform, but 7cot is a unique system built from the ground up to facilitate anonymous emotional support. Moreover, the hundreds of thousands of users present on 7cot enable a big data-driven approach to understand a population of users and the conversations they hold, rather than focusing on a small number of users.

III. Platform and Dataset Description

7cot was launched in December 2013 and is used by three types of users: *members* who register an account on the site to speak with someone because they face emotional distress, *listeners* who complete an online training program to listen to the problems of others, and *guests* who wish to speak to someone without registering on the site. We note that 7cot maintains a unique identifier for each guest, based on browser signature and a cookie, so that it can keep track of the activities of the same guest over multiple sessions. Guests and members have the option of identifying themselves as a teenager or an adult. The three types of users may communicate in a one-on-one conversation, a group chat room, or in a forum. A conversation is an asynchronous exchange of messages between a guest or member and a listener. In other words, although a conversation begins with the two participants exchanging messages in real time, it will persist after someone exits the system. This allows one participant to login and leave a message for the other user in the future. A conversation is *personal* if the user selects a specific listener to speak with. The conversation is *general* if, instead of picking a listener, the user asks the service to connect with any listener presently available. Guests and members have the option of filtering available listeners by particular topics they have expertise in handling, which are listed in Table I. Gamification mechanisms are used to reflect listener reputation and commitment to the community and quantify the growth and community interaction of the users. Further details about the operation of the site and about the effects of these gamification mechanisms are discussed in our previous work [8].

7cot provided a database capturing the attributes of all users, interactions, and activities performed since its inception on December 5th, 2013 until August 14th, 2015. The database includes features of all three types of users, except for those related to their true identity and contact information. Attributes of each conversation record were limited to participant identifiers, the date the conversation commenced, the number of messages exchanged by each party, whether the conversation was for a teenager or adult user, if the conversation was terminated or blocked by either party, and timestamps of the conversation request and of the last message sent.

Num. Users	297,151 (members); 1,043,821 (guests)
Num. Listeners	82,886 (members); 82,385 (guests)
Num. Member Conversations	403,903 (teen); 951,701 (adult)
Num. Guest Conversations	491,140 (teen); 1,231,414 (adult)
Avg. Num. of Conversations	4.56 (members); 1.65 (guests)

TABLE II: Volume of users and conversations

IV. User and Conversation Analysis

To understand the users and the conversations they hold, we explore the following questions: (i) *Who uses the platform?* Does this emotional support platform tend to attract very young or experienced users, where are they from, and does this support platform have a world-wide reach? (ii) *Whom do they converse with?* How do users and listeners choose each other to hold conversations, and are there patterns in this relationship formation that can be related to other online social systems? (iii) *How often do they converse?* Once connections are established, how often are they utilized? Do conversations tend to be persistent over time, or is a conversation a kind of one-time-only event? We search for answers to these questions next.

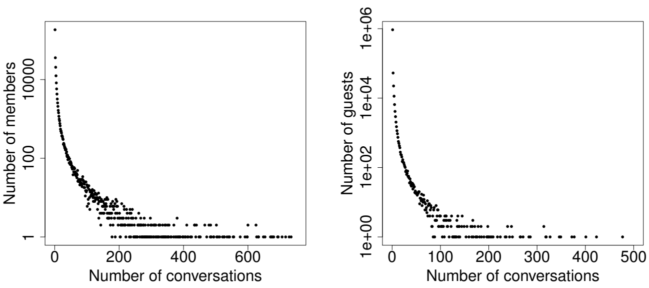
A. Who Uses the Platform?

The kinds of online emotional support systems examined in the literature focus on communities supporting a specific ailment or emotional problem. Demographic data about who uses these platforms, therefore, may be biased toward groups who have a greater tendency to suffer from the ailment. For example, users on a breast cancer support community may be more likely to be female since they have a higher likelihood of suffering from the disease compared to men. But since 7cot offers a space for people needing emotional support for *any* issue, demographic data about its users yield insights that speak to a general population of people needing emotional support. Due to space limitations, we focus our comparison on their age group, user type, and their geographic home.

1) Age groups: Controlling for whether a user self-identifies as an adult or teenager, Table II summarizes the number of members and guests, the number of listeners they hold conversations with, and the total number of conversations held. The table shows a very strong use of 7cot among teenagers, who represent 29.8% and 28.5% of member and guest conversations, respectively. This strong representation may be accounted by the fact that teenagers may be very comfortable using the Web as a communication medium, and hence, they have few reservations using an online emotional support system. Table II identifies 53% of all conversations as being initiated by guest users. It is interesting to note that members hold an average of 4.56 conversations, i.e., they tend to connect with about five different listeners to find

ADHD	Alcohol/Drug Abuse	Anxiety	Bipolar	Breakups	Bullying
Chronic Pain	College Life	Depression	Disabilities	Domestic Violence	Eating Disorder
Exercise Motivation	Family Stress	Financial Stress	Forgiveness	Getting Unstuck	Grief
LBGTQ+	Loneliness	Managing Emotions	OCD	Panic Attacks	Parenting
Perinatal Mood Disorder	Self Harm	Sleeping Well	Social Anxiety	Traumatic Event	Weight Management
Work Stress					

TABLE I: Topics of conversations held on 7 Cups of Tea



(a) Members (b) Guests

Fig. 1: Conversations held per member and guest

emotional support, whereas guests only hold an average of 1.65 conversations. This statistic may suggest that members seek out a diverse number of people to speak to, since each could offer a unique perspective or advice to address their problems. Given the large difference between the average of member and guest conversations, the process of registering and creating an identity on the online support service may be an important step for people to better utilize the platform, leading to better mental health outcomes.

We examine the distribution of the number of conversations held by members and guests in Figure 1. Both trends exhibit a number of outlying data points, where a tiny number of members and guests hold a very large number of conversations. They also experience an exponential decay on semi-log scale, indicative of heavy-tailed behavior [15], but at a slower rate for members compared to guests.

We investigated the outlying data points further and found that all members with more than 700 conversations have been *blocked* numerous times by a listener because of their inappropriate behaviors; blocked conversations are ones where either party completely and indefinitely terminates a conversation. Blocked data are not available for guests, but we postulate that guests having large numbers of conversations are also exhibiting inappropriate, spamming, or some other harassing behavior. It is thus difficult to conclude if the heavy tail is a natural phenomenon in the emotional support system, or if it emerges due to the behaviors of some exceptional users.

2) Listener locations and languages: Figure 2 visualizes the world-wide representation of the 90,901 distinct listeners on 7cot. Each country is colored if it is listed as the self-reported location of at least one listener in the database. We identify the largest population of listeners are in the US (42,449) or United Kingdom (12,099), but a number are also from India (5,540), Canada (5,404) and Australia (3,047). Listeners represent virtually every country in South America, Europe, the Middle East, and Asia. This distribution demonstrates a world-wide interest in helping others deal with emotional problems, no matter where the user is from. This is a boon for users seeking support, since they stand to benefit to listen to the advice of people who carry different cultural backgrounds and perspectives.

With information about the language a listener lists as being able to communicate in, we find over 137 different languages spoken on 7cot. This is another benefit for users, who are able to converse with listeners in their own language no matter where they are from in the world. Finally, as shown in Table III, almost 30% of all listeners converse in more than one language. English is the most commonly used language.

1	2	3	4	≥ 5
70.5%	22.5%	5.1%	1.3%	0.6%

TABLE III: Number of languages spoken by listeners

B. Whom do Users Converse With?

We next study the process by which users choose a listener for a conversation. Table IV summarizes conversation types chosen by members and guests controlling for if they are an adult or teenager. About one third of the conversations are personal, with a member or guest seeking help from a specific other, while two thirds involve an immediate connection with the first listener available. This suggests that the immediate availability of a person to speak to is more important to users than finding specific listeners based on their profile or experience. The table also shows that 17.2% of conversations are hidden, that is, archived or removed from the user's interface, and just 3.1% were blocked by a user. These statistics reflect the fact that conversations on the emotional support system are long-lasting, and that virtually all interactions are cordial.

We also find that the listeners users connect to are able and willing to receive training to support a wide variety of topics.

	Members		Guests	
	Adult	Teenager	Adult	Teenager
Num. general	542,011 (17.6%)	217,736 (7.1%)	936,490 (30.4%)	351,263 (11.4%)
Num. personal	409,690 (13.3%)	186,167 (6%)	294,924 (9.6%)	139,877 (4.6%)
Num. hidden	258,805 (8.4%)	79,655 (2.6%)	149,146 (4.8%)	41,605 (1.4%)
Num. blocked	40,931 (1.3%)	14,745 (0.5%)	30,843 (1%)	10,197 (0.3%)

TABLE IV: Breakdown of the 3,078,158 conversations initiated by members and guests according to their age and conversation type

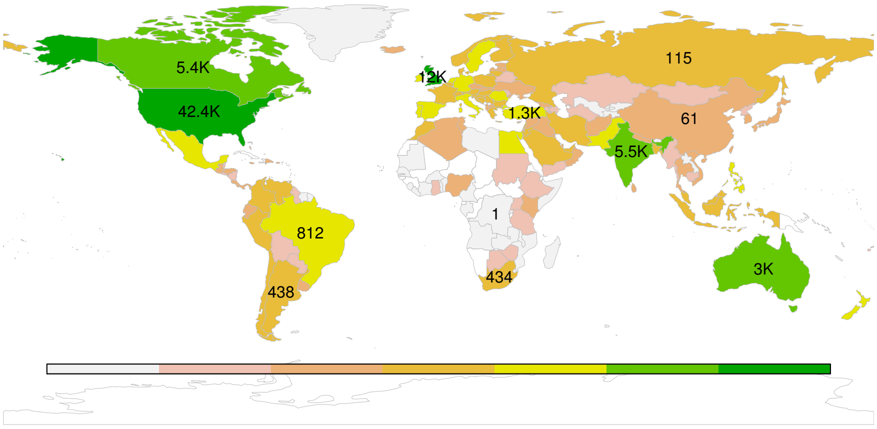


Fig. 2: Locations of 7cot listeners across the world

1	2	3	4	5	6
3%	5%	10%	12%	12%	12%
7	8	9	10	11	12+
11%	10%	8%	5%	4%	8%

TABLE V: Number of topics supported by listeners

For example, Table V shows that only 3% of all listeners can help about a single topic, whereas 67% of all listeners advertise an expertise in supporting between three and eight topics. In other words, listeners tend to be *generalists* trained to help others with a diverse number of topics, rather than *specialists* able to support just a single topic.

1) Evolutionary analysis: We further examine how conversations develop across the entire social system over time by building a tripartite interaction network where either a member or guest node is connected to a listener node if they hold a conversation. Of particular interest is whether the development of the network may be modeled by a preferential attachment process [16], where connections are more likely to be established with a node that already exhibits relatively high degree. Preferential attachment is a quality commonly exhibited in a number of large scale online social systems (see, e.g., [17], [18], [19]); observing preferential attachment on 7cot thus relates the mechanisms of user interactions on an emotional support service with other kinds of online social systems. To evaluate the presence of preferential attachment, we empirically compute the probability $p_e(d)$ that a member or guest u at time t will hold a conversation with listener v having degree d by:

$$p_e(d) = \frac{\sum_t \mathbf{1}(e_t = (u,v))\mathbf{1}(d_{t-1}(v) = d)}{\sum_t \mid \{v : d_{t-1}(v) = d\} \mid}$$

where e_t denotes a conversation created at time t, $d_{t-1}(v)$ the degree of listener v at time $t-1$, and $\mathbf{1}(\cdot)$ the indicator function. Figure 3 shows the overall probability $p_e(d)$ to connect to a degree d node on a log-log scale. It illustrates the emergence of a rich-get-richer phenomenon in the development of the network. We measure that the probability that an edge (conversation) is added to a node (listener) of degree d is proportional to d^α. In particular, the preferential attachment is somehow weaker for low degree nodes (i.e., $\alpha = 0.49$), whereas edges attach preferentially to higher degree nodes (i.e., $\alpha = 1.224$). This value suggests a super-linear preferential attachment, where once listeners connect with a number of others (in this dataset, approximately 100), they will asymptotically become connected to from all users on the service as their time t on the site goes to infinity.

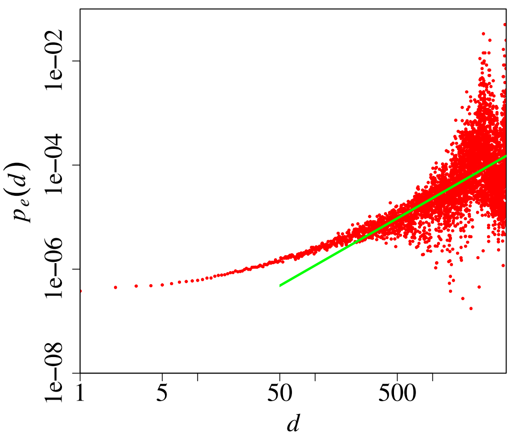
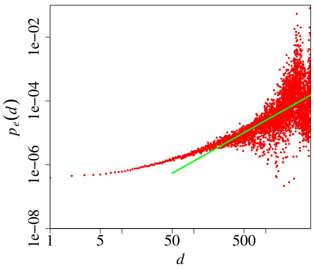
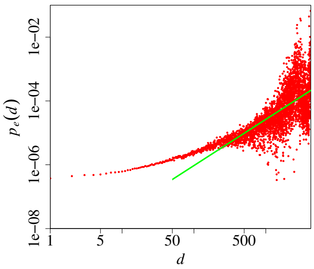


Fig. 3: Probability of connecting to a listener with degree d

Figure 4 checks for preferential attachment when the type of conversation (general or personal) is controlled for. It is interesting to find preferential attachment to hold for both types, although the phenomenon is more evident for personal conversations. The values of α for higher degree nodes are equal to 1.27 and 1.45 for general and personal conversations, respectively. We expected to observe this phenomenon for personal conversations because users select a listener based on a profile, which includes information about their experience and amount of activity on the site. Thus, it may be expected that a user will always choose a listener with more experience rather than one who has only helped a small number of others.



(a) General



(b) Personal

Fig. 4: Connection probability by conversation type

But finding preferential attachment for general conversations is surprising since the system automatically chooses an available listener, seemingly without regard for any characteristics of the listener. Preferential attachment in this case may be explained by a correlation between the number of conversations a listener holds and how often that listener is online and available on the site. It could also be indicative of an underlying mechanism on 7cot that prefers to match a more experienced listener when many are available at the same time.

That there is evidence of preferential attachment in the way users and listeners connected to each other is a kind of double-edge sword. On the one hand, it suggests that users needing support tend to connect to those listeners who have connected with many others, allowing them to accrue experience that helps them deliver more effective emotional support. On the other hand, because users tend to converse with listeners who already supported many others, it is difficult for listeners who are not supporting many users to accrue new ones in the future. Such listeners may thus be disinclined to continue logging in or volunteering their help on the service, posing a threat to the long term stability of the social system. For example, if the most popular or overburdened listeners decide to stop participating, a large proportion of users will no longer be supported, with a set of less experienced listeners remaining to pick up their efforts.

2) Communication densification: We also examine whether the network of conversations among users *densifies* over time. The densification of a network defines the extent to which more edges (conversations) rather than nodes (users) are added over time. Figure 5 plots in log-log scale the number of nodes (users and listeners) against the number of edges, per month, in the conversation network starting from December 2013. It indicates that densification is occurring, as the ratio of the number of edges to nodes grows as $e(t) \propto n(t)^{\alpha}$ where $e(t)$ and $n(t)$ denote the number of edges and nodes of the graph at time t. We measure the densification exponent α to be equal to 1.07. Densification underscores the need for users to communicate with a number of other listeners on an emotional support system. It also indicates that the scalability of the system hinges not on the number of users it can support, but on the number of conversations it fosters.

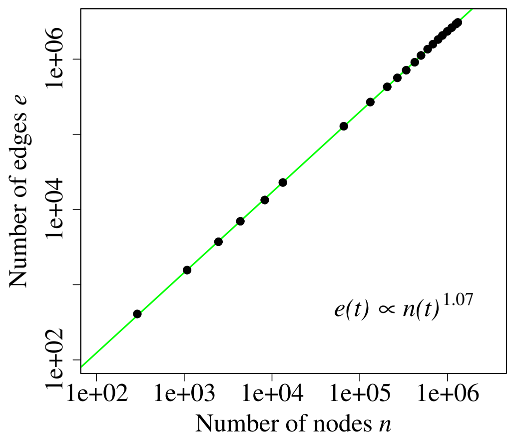


Fig. 5: Number of nodes and edges measured over time

C. How often do they converse?

Finally, we study when and how often conversations are initiated on 7cot. For this purpose, we counted the number of conversations created, on a weekly basis, since 7cot's inception and present them in Figure 6. It highlights how in the initial six months 7cot had little activity, but June 2014 signified a kind of tipping point where mass user adoption began. Ever since, the number of new conversations initiated has been growing. It is interesting to note that the emotional support platform is utilized regardless of whether a national or world holiday is being celebrated; for example, we find no significant variation in conversation frequency around holidays such as Christmas or New Year's.

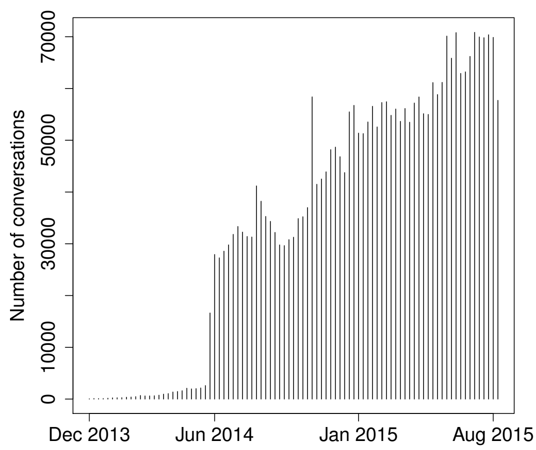
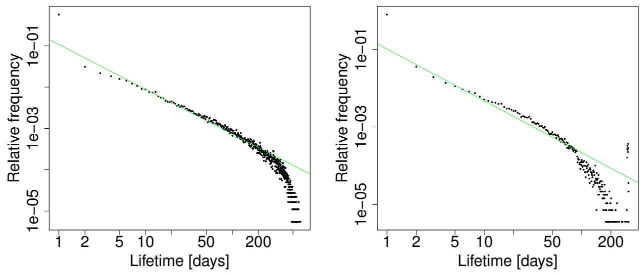


Fig. 6: Number of conversations per week initiated by 7cot users since its inception in Dec. 2013 until August 2015.

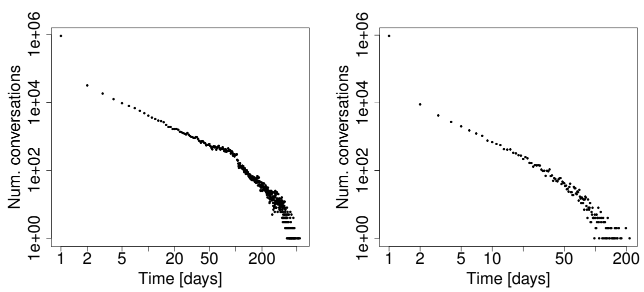
1) Conversation lifetimes: To assess how long users remain active in 7cot, we study their *lifetime*, that is the time elapsed between the first conversation and the last conversation created by a user in Figure 7. For both members and guests, we observe a clear peak (51.5% of members and 78.6% of guests) corresponding to a lifetime of one day. This reflects a tendency of some members and guests to initiate all conversations they will ever hold on a site within their first 24 hours. This behavior is not uniform, however, as we find the distribution to follow a power-law in the body with an exponential drop in the tail. This is indicative of a double-pareto lognormal (DPLN) distribution, which the duration of mobile phone calls are known to follow [20].



(a) Members (b) Guests

Fig. 7: Lifetime of members and guests

The time a conversation is active, that is, users and listeners exchange messages, is another interesting measure of the user activity on 7cot. The corresponding distributions, shown in Figure 8, also exhibit a DPLN-like shape. The mechanisms about how long people choose to converse with someone on the emotional support service is therefore quite similar to conversations over mobile phones, suggesting that the conversations may exhibit a very natural flow and length that are similar to what people would hold if they were discussing their problems over the phone.



(a) Members (b) Guests

Fig. 8: Time between the first and last message of the conversations

2) Message volume: We also examine the volume of messages sent during different conversations, which may be useful to evaluate a user's willingness to actually share information and to seek positive outcomes. Table VI shows that a total of 68,644,862 messages were shared by those needing help, with an average of 22.3 messages per conversation. However, guests

	Members		Guests	
	Adult	Teenager	Adult	Teenager
Num. general	14409346	3679397	10,968,358	2,892,668
	(21%)	(5.4%)	(16%)	(4.2%)
Num. personal	20959280	5610589	7,886,540	2,238,684
	(30.5%)	(8.1%)	(11.5%)	(3.3%)

TABLE VI: Breakdown of the 68,644,862 messages sent in one-on-one conversations by members and guests according to their age (i.e., adult/teenager) and conversation type (i.e., general/personal)

are far less willing to share compared to members, as they only submit an average of 14 messages per conversation. This reinforces the notion that guests exhibit a level of trepidation about participating on the emotional support service. The cumulative distribution of the total number of messages sent by members and guests is shown in Figure 9. For members, the figure shows that approximately 1% of the most talkative members account for 20% of all messages members sent, while the top 12.2% account for 80% of all messages. The Pareto principle [15] better holds for guests, where the 18.5% most talkative guests account for 80% of all messages guests sent.

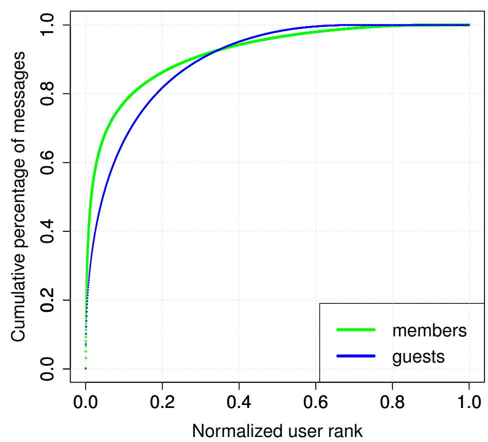


Fig. 9: CDF of message count for members and guests

Table VII summarizes the volume of messages sent by the listeners. Compared to the 68.6M messages sent by users, listeners send 63M messages, that is, 20.5 messages per conversation. This difference could be due to an "impatience" effect by users needing to talk about their problems, where they send many messages without waiting for the listener reply and leave messages for the listeners when they are offline.

	Members		Guests	
	Adult	Teenager	Adult	Teenager
Num. general	13,312,574	3,517,449	10,296,165	2,720,111
	(21.1%)	(5.6%)	(16.3%)	(4.3%)
Num. personal	18,714,234	5,453,439	6,983,880	2,016,695
	(29.7%)	(8.7%)	(11.1%)	(3.2%)

TABLE VII: Breakdown of 63,014,547 messages sent in one-on-one conversations by listeners according to conversation type and type of user involved

V. Conclusions and Future Work

This paper evaluated the users and the conversations they hold on a large scale, vibrant online social service. Measurements taken from the hundreds of thousands of users and millions of conversations revealed characteristics that not only provided general insights into who and how people utilize an online emotional support system, but also system features promoting its long-term viability. Specifically, our study found that the system is often utilized by teenagers, that users with an identity on the platform engage more often and could have better mental health outcomes, that heavy tails in the frequency of conversations per user may not be natural, that an emotional support system can have a massive, world-wide adoption, that connecting to any listener immediately is preferred to finding a specific listener, that nearly all listeners are willing and able to support a number of different emotional problems, that the preferential attachment process governing how users connect to listeners may actually be a long-term challenge of an emotional support system, that densification implies the need to scale a system to handle more conversations than users, and that the statistical nature of conversation lengths on the emotional support system is not unlike the lengths of mobile phone conversations.

Future research will dig deeper into the nature of the conversations being held, with a particular focus on those users who where blocked or banned from conversations due to harassment. To understand how an emotional support platform grows into a vibrant community, the structural evolution of 7cot will also be explored in more detail.

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