Effects of Support-Seekers' Community Knowledge on Their Expressed Satisfaction with the Received Comments in Mental Health Communities

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ABSTRACT

Online mental health communities (OMHCs) are prominent resources for improving people's mental wellbeing. An immediate cue of such improvement is support-seekers' satisfaction expressed in their replies to the received comments. However, the comments that seekers find satisfying may change with their community knowledge, e.g., measured by tenure and posting experience in that community. In this paper, we first model the amount of satisfaction conveyed in the support-seekers' replies to the received comments. Then we quantitatively examine how seekers' expressed satisfaction is affected by their community knowledge, sought and received support in an OMHC. Results show that support-seekers with more posting experience generally display less contentment to the received comments. Compared to newcomers, higher tenured members express less satisfaction when receiving informational support. We also found that support matching positively predicts seekers' satisfaction regardless of their community knowledge. Our findings have implications for OMHCs to satisfy support-seekers through their community knowledge.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**.

KEYWORDS

Mental health, online community, informational support, emotional support, tenure, familiarity, satisfaction, reply behaviors

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1 INTRODUCTION

Online mental health communities (OMHCs) provide a convenient platform for people with mental health challenges to exchange social support with peers [38, 45]. For example, in Reddit NoDepr [1], one can create a support-seeking post about depressing problems and interact with other community members who comment on the post. By tracking content and emotional changes in posts over a long period, researchers have found evidence that OMHCs are generally effective in improving their members' mental health, such as reducing depression [51, 61] and bringing positive cognitive change [58]. However, to obtain an immediate sense of whether the needs of members reaching out for help are met – a crucial determinant of their intention to stay in and get benefits from the community [38, 49, 63, 74], OMHCs would need to exploit more instantaneous cues, such as support-seekers' satisfaction with the received comments [70]. Satisfaction can be "the affective experience when expectation-type standards are fulfilled" (p. 357) [30], and it is commonly self-reported by people through questionnaires in contexts like customer services [6, 29, 56, 78]. In text-based communication in OMHCs, however, support-seekers usually do not rate their satisfaction but mostly acknowledge it in their replies to others' comments [70]. Communicating satisfaction in the replies can not only benefit the seekers by encouraging a deep conversation with others [41, 50] but also do good to support-providers by enhancing their sense of worthiness [9]. Therefore, to boost OMHCs' efficacy of improving members' mental health, it is necessary to understand the factors that would affect seekers' expressed satisfaction in response to the received comments.

[1] We use an anonymous name for privacy concern

Starting from the "expectation-type standards" in the definition of satisfaction mentioned above, one salient factor that may influence support-seekers' displayed contentment is their community knowledge. The seekers' community knowledge can be measured by how long they have stayed (denoted as **tenure**) and how many posts and comments they have created (**posting experience**) in that community [67]. As members stay longer and participate more in the group communication, they may have different expectations and perceived standards of the received comments in comparison to when they first came to the community [12, 75]. For example, Yang et al. revealed that the provision of informational support (**IS**, e.g., advice) and emotional support (**ES**, e.g., empathy) in the received comments increases members' commitment to an online cancer group more for members of lower tenure [75]. From "fulfilled" in the satisfaction's definition, the received support itself and the match between the type of sought and received support could also impact seekers' satisfaction. For example, Vlahovic et al. found that receiving IS or ES can positively predict expressed satisfaction in a health community for cancer [70]. However, few works have tried to understand whether and how the seekers' community knowledge itself and its interaction with received support (e.g., IS and ES) affect their satisfaction conveyed in the replies to others' comments in OMHCs. Such understanding is important and beneficial as it can deepen researchers' and psychologists' understanding of how members' behaviors and emotional states change over their time in OMHCs. Moreover, it can provide empirical evidence for OMHCs to design timely interventions to satisfy support-seekers' needs based on their tenure and posting experience.

In this work, we quantitatively investigate the effects of support-seekers' community knowledge (in terms of tenure and posting experience) as well as sought and received support (IS and ES) on their expressed satisfaction in response to the received comments in Reddit NoDepr, an OMHC for depression. To address the challenge of estimating seekers' satisfaction displayed in posters' replies, we first follow the method in [70] to conduct a crowd-sourcing task on $1,000$ post-comment-reply triples to label the amount of contentment in each reply. We then develop a supervised learning model to assess the amount of satisfaction expressed in a piece of text based on its linguistic features, and we apply this model to $155,067$ data samples. Next, using regression models, we explore the researcher questions (***RQ***): how would support-seekers' community knowledge, sought and received support affect **1)** whether support-seekers would reply to the received comment or not, and more of our focus in this paper, **2)** the extent to which they would express satisfaction in their replies.

Our results show that in general, support-seekers with less community knowledge are more likely to reply to the received comments, and those with less posting experience tend to express more satisfaction in response to the commenter, if at all. We found that support-seekers with varying degrees of tenure or posting experience differ in their amount of expressed satisfaction with the received support. For example, compared to the newcomers, those of higher tenure tend to express less satisfaction when receiving IS-related comments to their posts in the depression community, regardless of whether they want IS or ES. Also, we found that receiving IS or ES in a comment and the match between the type of sought and received support positively predict support-seekers' tendencies to convey satisfaction in the reply to that comment. Our findings add understanding of how the support-seekers' community knowledge influences their expressed satisfaction with the received comments. During the analysis process, we also contribute a machine learning model to estimate support-seekers' satisfaction expressed in their replies to other members of OMHCs.

2 RELATED WORK

We first motivate our work by the benefits of online mental health community (OMHC) and the importance of studying support-seekers' OMHC knowledge‘s effect on their satisfaction and then situate this paper in previous OMHC studies.

2.1 Benefits of Online Mental Health Communities

Online mental health communities offer a convenient way for people to exchange peer-to-peer social support with others in similarly challenging conditions [13, 48]. As a common practice, people go online to seek social support to relieve their distress and satisfy their psychological needs [19, 28, 38, 70], and others who are facing or have experienced similar problems provide help to the support-seekers [56, 67, 76]. The communication between these support-seekers and providers usually happened in the posted threads created by the seekers, with text as the conversational medium [28, 56, 67]. Previous research has suggested that participating in the communication in OMHCs could improve members' mental health [34, 46, 57, 58, 61, 64, 68]. For example, Rains et al. conducted a meta-analysis of computer-mediated support groups and found that long-term participation in such communities was associated with less depression, greater quality of life, and improved self-efficacy in managing their health conditions [61]. Morris et al. conducted a 3-weeks study with 166 participants and showed that those in an OMHC significantly reduce depression than those who use an expressive writing tool. [46]. Pruksachatkun et al. studied thread discussions in an OMHC and found that support-seekers can experience a positive cognitive change in peer-to-peer conversations [58]. Support-seekers' satisfaction with the received comments is also one symbol that indicates mental health improvement and can be quickly assessed from their replies to those comments [70]. We motivate our study by the benefits of OMHCs and choose to evaluate seekers' satisfaction with the received comments to understand the immediate outcome of thread communication.

2.2 Support-Seekers' Knowledge of the Community

Members' community knowledge can be defined by their familiarity, awareness, or understanding of things (history, norms, etc) in that community [31]. We follow [67] to measure it by members' tenure in and posting experience with that community. Tenure reflects how long the member has stayed in the community and the one who stays longer should know more community history. Posting experience indicates how many posts and comments the member has created in that group [67] and such interaction can normally boost knowledge acquisition [31]. Therefore, members with higher tenure and more posting experience are supposed to have more community-relevant knowledge. Exploring the relationship between seekers' community knowledge and their satisfaction can provide insights for OMHCs to offer better services to members based on their community knowledge. For example, if newcomers tend to express less satisfaction, OMHCs can consider assigning more supportive peers to their posts.

Previous works suggest that support-seekers' community knowledge could affect their expressed satisfaction in two directions. In one direction, support-seekers with more community knowledge would be less likely to express satisfaction in response to the received comments. The theory of diminishing marginal utility [32] details how the marginal utility (i.e., the change of benefit derived by an action [32]) of each new unit of communication should vary inversely with the amount of communication the members have previously experienced, as shown in many other contexts [23, 43]. For example, users with more friends on Facebook gain less social capital benefits when they get a new friend [23]. Comments from others might be more valuable for the new members as those with more community knowledge are likely to have seen similar content before. Thus, it is plausible that support-seekers with less community knowledge would express more satisfaction in their replies.

In another direction, however, experienced support-seekers would engage more actively and positively in their threads. From the Attraction-Selection-Attribution organizational function model [65], members are more likely to stay in a group when it matches their attributes and satisfies their needs. Moreover, they might be more aware of the benefits of replying positively to others in their threads, which helps to build a likable social image and strengthen their connections with others [39]. Thus, support-seekers who have stayed longer and created more posts in the community may find it more rewarding to communicate with others positively in their threads.

Given these two possible directions of community knowledge's effects on support-seekers' satisfaction with the received comments, we are interested in exploring which direction it will go in an OMHC for depression.

2.3 Studies of Online Mental Health Communities

A large amount of research has widely explored the characteristics and dynamics of OMHCs. For example, Cutrona et al. divided the exchanged social support into several types such as informational support (noted as **IS**, e.g., information or advice), emotional support (**ES**, e.g., empathy, love, or concern), and network support (e.g., belonging to a group of people) [18]. Among these types of social support, IS and ES are the most prominent and attract researchers' attention [56, 67, 72, 75], e.g., Ridings and Gefen found that 76% of members join online health groups to exchange IS and ES [62]. Sharma et al. built classifiers to identify the IS and ES offered to support-seekers in 55 OMHCs in Reddit and found that the distribution of IS and ES vary across the community categories (e.g., "Mood Disorder" and "Psychosis & Anxiety") [67]. They further showed that the support-seeking posts tend to attract more IS and ES if their text follows that community's common linguistic practices [67]. Chancellor et al. employed language modeling to compare the linguistic norms between two health communities and found differences that suggest different behavior change goals in these groups [12]. As members with more community knowledge may be more aware of the linguistic norms, these works imply that seekers' community knowledge could affect how they react to the received comments. There are also studies that analyze the effects of received IS and ES on members' commitment [75], how members' roles change during their lifecycle in the community [76], how seekers' self-disclosure and received support differ in public and private channels [77], and how received support and support matching influence seekers' satisfaction expressed in their replies [70]. For example, Vlahovic et al. found that users express more satisfaction when sought and received IS in an online cancer group [70], and Yang et al. showed that members frequently change roles from support-seekers to providers over their history in another cancer support community [76]. Other studies have explored OMHC topics about members' disclosure [8, 24, 42, 54, 55], culture [38, 79], members' perception [21, 52] and behaviors [22, 53], and content detection [69] and moderation [26]. We situate our study within the context of these previous works and fill in the understandings of how support-seekers' community knowledge would affect their satisfaction expressed in the replies to received comments with IS and ES.

3 METHODS

This work systematically studies the effects of support-seekers' community knowledge, sought and received support on their expressed satisfaction in response to the comments. As seekers may not reply to their received comments and the act of replying may reflect satisfaction [70], we include "reply or not" in our research questions (Fig. 1):

RQ. *How would support-seekers'* ***community knowledge, sought and received support*** *affect whether they will* ***1) reply or not*** *and how they* ***2) express satisfaction*** *with each received comment in an OMHC for depression?*

Ethics and Researcher Disclosure: We shape the work by our experience with and observation on people who encounter mental health problems. The authors have experience of seeking and providing support online and realize the importance of our topic for OMHCs. One of the authors has a mental health first aid certificate and guides our approach. Prior to this work, our research team obtained IRB approval for broader research projects on patients' and caregivers' practices of healthcare service systems and online communities, which cover our data collection and analysis. We take several steps to protect participants' privacy. First, we remove the information of post authors and the community when we ask the trained coders or crowd-sourced workers to label our data, e.g., the amount of satisfaction expressed in the seekers' replies. Second, we do not include any personally identifiable information, e.g., email, gender, and address, during the data collection process. Further, we conduct all analyses with masked usernames.

3.1 Research Site and Dataset

To address the research questions above, we use data from the Reddit NoDepr – an online mental health community (OMHC) with over 400k members as of 2019. The NoDepr has been designed

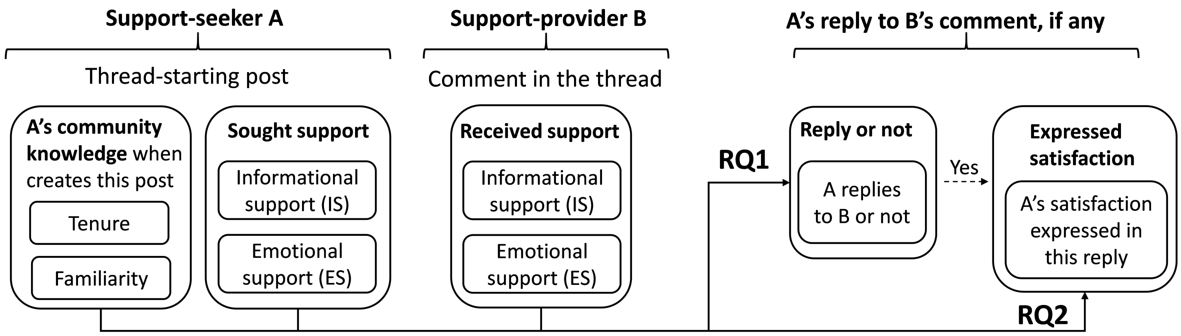


Figure 1: Conceptual model of research questions: the effects of support-seekers' community knowledge and sought and received support on their RQ1) reply behaviors to and RQ2) expressed satisfaction with each received comment.

as an anonymous place for anyone struggling with depression to exchange peer support. Typically, the original posters who start the discussion thread will describe their depression issues in their initial post [56, 67]. Throughout our paper, we refer to *support-seekers* as the original posters of the threads and support-providers as those who respond to the seekers. In addition, when we use "*post-comment*" pair or "*post-comment-reply*" triple in the paper, the "post" is the thread-starting post created by support-seekers, the "comment" is any support-providers' message in that thread, and the "reply" is the support-seekers' response to that received comment on their threads (Fig. 1). We do not restrict the comment to be the first response to the thread-starting post, because we are interested in assessing whether and how support-seekers would reply to a comment in their threads, regardless of its position.

We collect publicly available posts and comments created between Jan 2009 to Mar 2019 in this OMHC via Pushshift API [59]. We take two steps to pre-process the collected data. First, we remove the threads in which the support-seekers' names are "[deleted]" since we cannot track their community knowledge. Then, we remove the post-comment pairs and post-comment-reply triples in which the content of either post, comment, or reply is "[deleted]" or "[removed]" [27]. After pre-processing, our dataset consists of 124, 837 support-seekers with 201, 352 unique thread-starting posts that have at least one comment. These posts get a total of 590, 158 comments from support-providers, forming 590, 158 post-comment pairs (labeled as 1 if the comment gets a reply from the seeker; otherwise 0) that are used for RQ1 about whether the seekers reply or not (Table 1). The post-comments that get seekers' replies provide us 155, 067 post-comment-reply triples for analyzing RQ2 about expressed satisfaction in the replies.

3.2 Developing a Model to Assess Expressed Satisfaction in the Reply

3.2.1 Labeling satisfaction. To collect the labels for the amount of expressed satisfaction in the support-seekers' reply, we follow [70] to deploy a crowdsourcing task with 1,000 randomly sampled post-comment-reply triples on Amazon Mechanical Turk [1]. We only include workers with a US location and an 85% approval rate for their previous works. Workers first read the task instructions and go through a task demo. They then finish a HIT of five labeling sessions one by one, where a HIT stands for Human Intelligence Task that a worker can complete in MTurk [1] to get a reward - $0.42 for around 3.5-minutes workload in our case; US min wage of $7.25 per hour in 2020. In each session, they read one post-comment-reply triple and answer four questions about the support-seeker's satisfaction expressed in the reply, i.e., overall satisfaction, satisfaction with the received health information, change in sentiment, and change of closeness to the other members of the community [58, 70]. These questions are measured on 7-point Likert scales, with either "1 - Completely dissatisfied, 7 - Completely satisfied" or "1 - Decreased very much, 7 - Increase very much". To check if workers perceive politeness [10, 11] and satisfaction as the same concept, we also ask them to rate the support-seekers' politeness in each reply ("1 - Very impolite, 7 - Very polite"). To increase the workers' attention and to control qualities, in each session, they need to answer two identical questions on overall satisfaction (ratings should not differ over two points) and select a required option in a specific question. Eventually, each of the 1,000 triples is labeled by five different workers. The four questions about satisfaction form a highly reliable composite satisfaction scale (Cronbach's alpha = 0.90), which is the average of the four ratings. The five workers have consistent agreement on the composite satisfaction in the same reply (intra-class correlation is0.80). We average the composite score from five workers for each reply as the final label of expressed satisfaction ($M = 4.35, SD = 1.05$; min/max = 1.40/6.65). While the average rating of politeness ($M = 4.97, SD = 1.02$) in the reply positively correlates with the composite satisfaction score (Pearson $r = 0.766$), its mean is significantly higher than that of satisfaction ($t(1998) = -14.18, p < .001$). It indicates that the expressed politeness and satisfaction are two related but different concepts from the crowd workers' points of view. In the following analysis, we only focus on seekers' expressed satisfaction.

3.2.2 Predicting expressed satisfaction. To estimate the extent of satisfaction expressed in the reply, we build a linear regression model following [72] which uses the comments' linguistic features to predict their quality of support in a cancer support group. The model inputs linguistic features of the replies, including 65 features from the LIWC 2015 library [2, 56, 60, 67], sentence/word count [56, 72], frequencies of words in the keyword sets [72] "trial" (e.g., try, tried), "unknown" (e.g., what to do, not sure), "lonely" (e.g.,

	Number	Count of Support-Seekers	Targeted Dependent Variables	Targeted RQ
Post-comment pairs	590,158	124,837	Reply or not	RQ1
Post-comment-reply triples	155,067	57,881	Expressed satisfaction	RQ2

Table 1: Descriptive of our dataset. Here, "post" is support-seekers' thread-starting post, "comment" is any support-providers' message in that thread, and the "reply" is the support-seekers' response to that received comment.

alone, no friend), "sadness" (e.g., sad, pathetic), "feel" (e.g., feel), "negation" (e.g., not, never), "excited mark" (!, :)) , "thankful" (e.g., thank you, it helps) and "agreement" (e.g., Me too, feel similar) [2]. The 1,000 labeled replies are randomly partitioned into train (80%), validation (10%), and test (10%) sets. After the model is tuned to achieve good performance on the validation set, we evaluate how well the final regressor works in the test set. The Pearson correlation between the predicted and human-coded satisfaction of the 100 replies in the test set is 0.72, indicating a strong, positive correlation. We apply this regressor to estimate the expressed satisfaction in the 155,067 replies in the RQ2 dataset.

3.3 Community Knowledge in Terms of Tenure and Posting Experience

We follow [67] to quantify the community knowledge in terms of tenure and posting experience. ***Tenure*** is calculated as the time difference between the timestamp of support-seekers' first post/comment in the community and that of their current post [2, 67]. It is a slightly different definition of tenure from that in [75] (time of current post minus the registration time) as we are not able to access the members' registration time. Yet, the larger value of tenure means that the support-seekers stayed longer in the community when they created that post. ***Posting experience*** is the number of posts and comments created by the support-seekers in the community before the current post [67]. The larger number indicates that the support-seekers have more experience in posting and commenting in that community. For each thread-starting post in our dataset, we calculate the tenure and posting experience of the support-seeker when he/she created that post. The support-seekers are supposed to have more community knowledge if they were both of higher tenure and more posting experience in the community.

3.4 Amount of Sought Support in Thread-Starting Post

Following the well-developed methods in [56, 67, 75, 77], we rate a random sample of 500 thread-starting posts for the amount of sought informational support (IS) and emotional support (ES) in a three-point scale (1 - small, 2 - medium, 3 - large; similar to [56, 67]). We recruit three annotators (males, age: 23, 23, 24) who have labeling experience on OMHC posts before. They first rate 50 random samples separately and then discuss and generate a consistent rating scheme (e.g., sought IS = 1 if the post does not seek information or advice; sought IS = 3 if the post directly asks for advice) [3]. Next, they apply the rating scheme to the 500 posts independently. The human judges on the ratings of 500 posts are very reliable, with Cronbach's alphas of 0.91 and 0.81 for seeking IS and ES. We resolve the disagreement by majority vote and discussion. Finally, we have 189 (160), 127 (199), 184 (141) posts labeled as a small, medium, and large amount of sought IS (ES), respectively. We train two classifiers for sought IS and ES using a set of linguistic features (e.g., LIWC, sentence/word count) commonly employed by works on health community content analysis [56, 67, 72, 75]. Among the SVM, Multinomial Logistic Regression, Random Forest, XGBoost, and Multi-Layer Perception (MLP) models, XGBoost/MLP achieves the best result in predicting IS/ES in terms of mean accuracy (70%/65%) and mean F1 score in the 10-fold cross-validation [4] (Table 2). In a cross-verification on another 100 posts, the classifiers achieve a 73% accuracy for seeking IS and a 66% accuracy for ES in this process. Given the appropriate validity of these classifiers, we then apply them to estimate the amount of sought IS and ES in each thread-starting post of the 590,158 post-comment pairs.

3.5 Amount of Received Support in the Comment under the Thread-Starting Post

We adopt the models open-sourced by Peng et al. [56] who build a bot to provide writing feedback based on the predicted IS and ES of comments. The models have a 64 % accuracy for predicting IS (a random forest model) and a 68% accuracy for classifying ES (an XGBoost model) provided in the comments (1 - small, 2 - medium, 3 - large amount). Their training data is randomly sampled from a similar research site for depression used in our study. Given the appropriate validity of these models and the same nature of the dataset, we apply them to classify the amount of IS and ES in each comment of the 590,158 post-comment pairs.

4 ANALYSIS AND RESULT

We address our research questions via two sets of regression analyses, with Analysis 1/2 for RQ1/RQ2 (statistics in Table 3). All the independent variables (IVs) in the analyses are standardized for factor comparison, with a mean of zero and a standard deviation of one. To check for multicollinearity, we calculate the correlations between each pair of IVs (Fig. 2). Also, we calculate the variance inflation factor (VIF) score of each variable in the regression models, and the results indicate that multicollinearity is not a problem for any of the regression models in the analyses (VIF < 5).

Robustness Check. As a robustness check to rule out other possibilities that might explain our IVs' influences on the dependent variables (DVs) in each RQ, we perform additional regression analyses under a random setting for each set of models in Analyses 1

[2] The features and the weights for frequencies are chosen first by relevance and then by trial and error. The features and the model are attached in the supplementary materials and will be open-sourced in the future.

[3] The rating scheme for sought support is in http://zhenhuipeng.com/projects/satisfaction_mental_health/Sought_support_rating_scheme.pdf

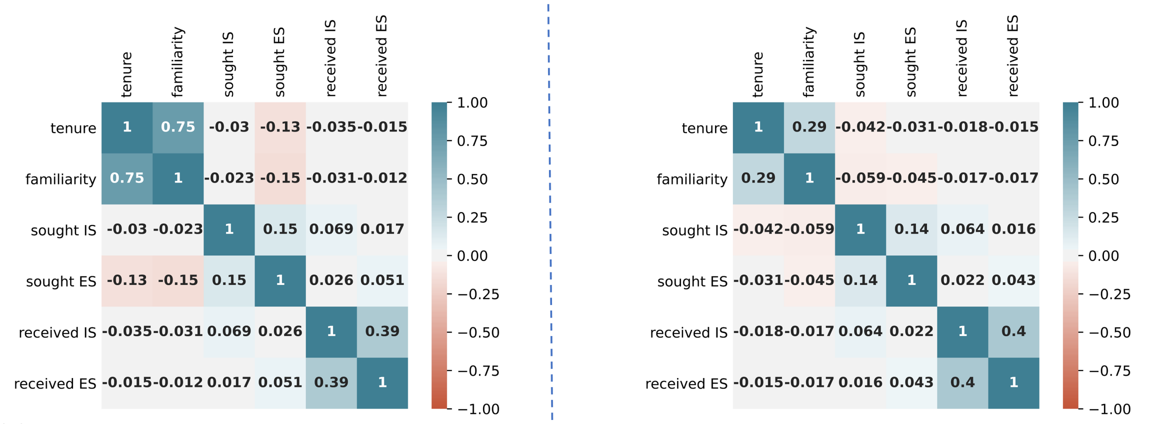
[4] The features of models can be found in http://zhenhuipeng.com/projects/satisfaction_mental_health/feature_sets_for_satisfaction_and_sought_support_models.pdf, and the models are in http://zhenhuipeng.com/projects/satisfaction_mental_health/source_codes.zip

	Accuracy	Precision	Recall	F1-score
Sought Informational Support	0.70 (0.05)	0.69 (0.06)	0.68 (0.06)	0.68 (0.06)
Sought Emotional Support	0.65 (0.12)	0.66 (0.11)	0.65 (0.14)	0.64 (0.12)

Table 2: Performance metrics for IS classifier (an XGBoost model) and ES classifier (a Multi-Layer Perception model) for assessing the amount of sought support in support-seekers' thread-starting posts. The μ (σ) are reported based on a 10-fold cross-validation.

		(RQ1) Dataset for replying or not (N = 590, 599)			(RQ2) Dataset for expressed satisfaction (N = 155, 174)		
	Variables	**Min / Max**	**Mean (SD)**	**Median**	**Min / Max**	**Mean (SD)**	**Median**
Community Knowledge	tenure (sec)	0 / 291M	16M (36M)	19M	0 / 272M	12M (24M)	1.5M
	posting experience (#)	0 / 3553	68.66 (340.21)	3	0 / 3553	36.60 (131.46)	4
Sought Support	sought IS	1 / 3	1.97 (0.88)	2	1 / 3	2.01 (0.87)	2
	sought ES	1 / 3	1.95 (0.79)	2	1 / 3	1.99 (0.78)	2
Received Support	received IS	1 / 3	1.74 (0.74)	2	1 / 3	1.84 (0.76)	2
	received ES	1 / 3	1.98 (0.66)	2	1 / 3	2.03 (0.68)	2
Seekers' Reply	reply or not	0 / 1	0.26 (0.44)	0	1 / 1	1 (0)	1
	satisfaction	-	-	-	-.56 / 8.17	4.31 (0.71)	4.22

Table 3: Descriptive statistics of variables for predicting support-seekers' reply behaviors to and expressed satisfaction with comments (RQ1&2). The min/max value of satisfaction slightly exceeds the scale of 1 - 7 as the satisfaction model is a regression model.



(A) Correlations between independent variables in RQ1 dataset for replying or not (*N = 590,158*).

(B) Correlations between independent variables in RQ2 dataset for expressed satisfaction (*N = 155,067*).

Figure 2: Correlations between each pair of independent variables in our dataset.

and 2. For example, to test the potential correlations between post-comment pairs and seekers' reply behaviors, we construct a corpus similar in size to the RQ1 dataset (Table 1). That is, instead of using the true label of getting a reply (i.e., 0 or 1) for each post-comment pair, we randomly assign a label from the entire corpus. We run the same regression analysis for Analysis 1 on the simulated dataset and find no significant effects between all the IVs and the DV – reply or not. Similarly, we simulate a corpus in which we randomly select a reply from the corpus to replace the original reply in each post-comment-reply triple. We conduct the same regression analyses for Analysis 2 on the simulated corpus and do not obtain a strong correlation between any IV and expressed satisfaction.

4.1 Analysis 1: Reply to the Received Comment or Not

Analysis 1 uses a set of hierarchical, random-effects regression models to investigate whether the support-seekers would reply to each received comment on their threads. We use logistic regression to analyze 590, 158 post-comment pairs since the dependent variable is binary. The independent variables are community knowledge (i.e., tenure and posting experience), sought support in the thread-starting post (i.e., seek IS and ES), received support in the comment (i.e., receive IS and ES), the interactions between sought and received support [70], and the interactions between community knowledge and received support. As members with different tenure may have created the same amount of posts and members, we add

	Models for RQ1 – Reply or not				
Predictors	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Tenure	-.106***	-.102***	-.101***	-.098***	-.099***
Posting Experience	-.116***	-.110***	-.113***	-.108***	-.107***
Post Frequency	.024***	.025***	.025***	.026***	.026***
Seek IS		.047***		.037***	.037***
Seek ES		.044***		.041***	.041***
Receive IS			.157***	.154***	.158***
Receive ES			.023***	.021***	.020***
Seek IS x Receive IS				-.008**	-.008*
Seek IS x Receive ES				.006	.006
Seek ES x Receive IS				.004	.006
Seek ES x Receive ES				-.012***	-.013***
Tenure x Receive IS					.009
Posting Experience x Receive IS					.022***
Tenure x Receive ES					-.003
Posting Experience x Receive ES					-.011
Intercept	-1.042***	-1.043***	-1.048***	-1.049***	-1.050***
R Square	0.004	0.005	0.009	0.010	0.010

Table 4: Regression coefficients of RQ1 models for predicting whether support-seekers' would reply to the received comments or not. The numbers of users are $124,837$**. The numbers of observations are** $590,158$**. Here, ***:** $p < 0.001$**; **:** $p < 0.01$**; *:** $p < 0.05$**.**

a control variable "post frequency" (posting experience divided by tenure) to our models.

Model 1 in Table 4 shows the main effects of support-seekers' community knowledge on whether they would reply to received comments or not. The coefficient for post frequency ($\beta = 0.024$) shows that members who actively create posts and comments are more likely to respond to the received comments. However, holding instant this individual difference, the coefficients for tenure ($\beta = -0.106$) and posting experience ($\beta = -0.116$) show that the support-seekers with less community knowledge are more likely to reply to the received comments in their threads. Models 2 and 3 add the effects of types of sought and received support, respectively. As indicated by Model 2's coefficients, people are more likely to reply to others when they seek a larger amount of informational support (IS, $\beta_{IS} = 0.047$) and emotional support (ES, $\beta_{ES} = 0.044$) in the thread-starting post. The main effects of received support on seekers' reply behaviors are also significantly positive – the more IS ($\beta_{IS} = 0.157$) and ES ($\beta_{ES} = 0.023$) provided in the received comments, the more likely the support-seekers are to reply to the comments. This positive effect is especially apparent for the factor "receiving IS" whose coefficient ($\beta_{IS} = 0.157$) is the largest among all independent variables, suggesting that the provision of IS in a comment could largely trigger the support-seekers to reply to the providers.

Model 4 adds the interactions between the sought and received support. Interestingly, the match between the types of sought and received support negatively predicts the probability of that support-seekers reply to the comments ($\beta_{IS} = -0.008, \beta_{ES} = -0.012$). People are equally likely to reply to the providers when they seek IS but receive ES ($\beta = 0.006, p > 0.05$), or they seek ES but receive IS ($\beta = 0.004, p > 0.05$). The interactions between community knowledge and received support in Model 5 further indicate that when receiving IS, the support-seekers who have more posting experience in the community are more likely to reply ($\beta = 0.022$) than those with less posting experience.

4.2 Analysis 2: Support-Seekers' Expressed Satisfaction in the Reply

Analysis 2 focuses on RQ2 about the support-seekers' satisfaction expressed in their replies to the received comments. It uses hierarchical, random-effects, linear regressions to analyze $155,067$ post-comment-reply triples. Similar to Analysis 1, the independent variables include community knowledge (i.e., tenure and posting experience), sought IS and ES in the thread-starting post, received IS and ES in the comment, the interactions between support sought and received [70], and the interactions between community knowledge and received support. We also add the post frequency (posting experience divided by tenure) as a control variable to the models in Analysis 2.

The control variable – post frequency – does not have any significant effect on the expressed satisfaction in all the five models ($\beta = 0.000, p > 0.5$). Model 1 in Table 5 describes the main effect of community knowledge on the expressed satisfaction in the replies. As indicated by the coefficients, support-seekers with more posting experience in the community would convey less satisfaction in their replies ($\beta = -0.092$). Tenure of the seekers does not predict the amount of their satisfaction in their replies ($\beta = -0.005, p > 0.5$). Models 2 and 3 in Table 5 include the effects of sought or received support. Consistent with the case of the online cancer community in [70], people tend to express more satisfaction when they seek IS ($\beta = 0.020$) in their initial posts. However, if they seek ES ($\beta = -0.025$), they are about to display less contentment when they reply to others' comments. Also, people express more satisfaction with the comments that provide more social support, but the effect is an order of magnitude larger for receivedES ($\beta = 0.080$) than

Predictors	Models for RQ2 – Expressed Satisfaction **Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Tenure	-.005	-.004	-.003	-.003	-.002
Posting Experience	-.092***	-.092***	-.088***	-.089***	-.091***
Post Frequency	.000	.000	.000	.000	.000
Seek IS		.020***		.017***	.017***
Seek ES		-.025***		-.028***	-.028***
Receive IS			.013***	.011***	.010***
Receive ES			.080***	.081***	.079***
Seek IS x Receive IS				.018***	.018***
Seek IS x Receive ES				-.003	-.002
Seek ES x Receive IS				-.002	-.004
Seek ES x Receive ES				.005*	.004*
Tenure x Receive IS					-.011***
Posting Experience x Receive IS					-.002
Tenure x Receive ES					-.003
Posting Experience x Receive ES					-.019***
Intercept	4.305***	4.305***	4.298***	4.299***	4.300***
R Square	0.003	0.004	0.018	0.021	0.021

Table 5: Regression coefficients of RQ2 models for predicting support-seekers' expressed satisfaction in the replies to the received comments. The numbers of users are 57,881**. The numbers of observations are** 155,067**. Here, ***:** $p < 0.001$**; **:** $p < 0.01$**; *:** $p < 0.05$**.**

received IS ($\beta = 0.013$), indicating that ES could be the most valuable factor for satisfying members in this OMHC.

Model 4 adds the interaction between sought and received support and shows that the match between the types of sought and received support positively predicts expressed satisfaction in the replies ($\beta_{IS} = 0.018, \beta_{ES} = 0.005$). There is no significant interaction on satisfaction between seeking IS and receiving ES ($\beta = -0.002$) and between seeking ES and receiving IS ($\beta = -0.003$). These results are partially different from the case of the online cancer group examined in [70], in which the match between sought ES and received ES is not a significant predictor of satisfaction, and the users express less satisfaction when they seek IS but receive ES. It suggests that compared to people in online cancer groups, those in OMHCs for depression may be more appreciative if their emotional need is satisfied by others.

Model 5 in Table 5 examines how the interactions between community knowledge and received support affects support-seekers' expressed satisfaction. The coefficients indicate that higher tenured support-seekers who receive IS from the comments would express less satisfaction than the lower tenured ones ($\beta = -0.011$). Also, seekers who have more posting experience in the community tend to express less satisfaction when receiving ES ($\beta = -0.019$).

5 DISCUSSION

In this paper, we first build a machine learning model to estimate the extent to which support-seekers express satisfaction in response to the received comments in an online mental health community (OMHC) for depression. We then investigate the effects of seekers' community knowledge, sought and received support on their reply behaviors to and expressed satisfaction with the comments. This section further discusses about possible explanations of our experimental findings, design considerations for OMHCs to satisfy their members, limitation of this research, and proposed future work.

5.1 Support-Seekers' Community Knowledge and Satisfaction

The most notable findings of our work lie in the relationship between support-seekers' community knowledge and their conveyed satisfaction with the received comments. From Model 1 in Table 5, we can see that seekers with more posting experience generally tend to express less satisfaction about the comments under their threads. This finding supports the adaptation of diminishing marginal utility theory [32] in OMHCs, positing that the marginal benefit of each instance of communication decreases as the members experience more in the community. On the contrary, it is inconsistent with the Attraction-Selection-Attribution model of organizational function [65], which implies that members with a larger amount of community knowledge would be more positive to others as they learn the benefits of doing so. Furthermore, we show in Model 5 (Table 5) that support-seekers who created fewer posts before might value the received emotional support (ES) more than the experienced ones. When receiving informational support (IS), the higher tenured (which does not necessarily mean more posting experience) seekers are less likely to express high satisfaction than newcomers. These could possibly be explained by the fact that people who have more posting experience may get used to the wording of ES, and that people who stay longer in the community are more likely to have seen similar IS (e.g., advice) from the community before. Generally speaking, members join an online (mental) health community mainly to seek social support at the beginning [28, 62, 75], and any type of support presented in response to their requests would be appreciated. Our results raise questions as to why support-seekers have such different replying behaviors to the received comments over their time in OMHC, which need further in-depth interviews with the seekers.

5.2 Support Provision and Matching

Apart from the main findings above, we also confirm that peer provision of IS and ES is generally beneficial [38, 70, 72, 75] by showing that the amount of received IS and ES support positively correlates with their tendency to reply and communicate satisfaction to the providers. This indicates that comments with high IS and ES benefit both support-seekers who get satisfied and providers who get feedback of their comments. We notice that the coefficients (β) for receiving IS and ES are quite different in our regression models for support-seekers' reply behaviors and for extent of expressed satisfaction. More specifically, $\beta_{IS}(0.157)$ is larger than $\beta_{ES}(0.023)$ in Model 3 (Table 4) for predicting whether support-seekers' will reply to the comment or not, which suggests that receiving IS could be a stronger indicator for their desire to communicate with others further. However, when seekers do reply to the received comment, the provision of ES ($\beta = 0.080$) in that comment becomes a more important signal than providing IS ($\beta = 0.013$) for predicting their expressed satisfaction (Table 5). While Sharma et al. found that overall OMHCs like NoDepr in our case offer more ES than IS [67], our finding further indicates that showing ES in the comments could potentially elicit more support-seekers' satisfaction in reciprocity than presenting IS.

As for the sought support in thread-starting posts, our observations show that seeking IS is a positive predictor of the original poster's conveyance of satisfaction with the received comment but seeking ES is a negative predictor (Model 2 in Table 5), consistent with the findings in online cancer groups [70]. One possible explanation could be that people seeking ES might have longer-term needs than those who seek IS [72] and thus need more prolonged interaction to be satisfied. Nevertheless, when the type of received support matches the sought one, support-seekers are likely to convey more satisfaction. It is consistent with the results in [3, 71] and supports the Optimal Matching Theory, in which Curona et al. argued that certain types of social support may be more effective when corresponding to the types of requests [16]. Another interesting finding is that the match between sought and received support negatively predicts that seekers would reply to the comment (Model 4 in Table 4). This could be due to that people have already gotten what they needed from the comments and may lack motivation to converse further. Our findings may be applicable to a wide variety of OMHCs especially those related to different types of mood disorders (e.g., the OMHCs about suicide in Reddit), as the distribution of received IS and ES in these OMHCs is similar to that in the NoDepr community about depression [67].

5.3 Design Considerations

Our findings and the model for estimating expressed satisfaction in the reply offer several design considerations for OMHCs to engage and satisfy support-seekers in threaded communication.

5.3.1 Eliciting Experienced Support-Seekers' Feedback to the Received Comments. In general, more experienced support-seekers in our work are less likely to reply to the received comments, and if they do, they tend to express less satisfaction than those who have less prior posting experience. Despite that this might be a natural phenomenon as support-seekers become more senior in the community, the lack of positive feedback could discourage the support-providers [47] and reduce the chance of having a deep follow-up chat [50, 66]. OMHCs may consider gently elicit feedback from experienced support-seekers when they receive a comment. For example, a bot can send a prompt to ask how they feel about the comment. If they are satisfied with it, the bot can further invite seekers to show their contentment in response by explaining the potential benefits (e.g., build a connection [39]) of doing so. If they are not, the bot could act as a friend to comfort the seekers and encourage them to disclosure their feeling to the bot [35–37]. However, designers should be aware that such technological interventions could potentially bring additional labor to the support-seekers [26] and frustrate support-seekers who are sensitive of being judged in OMHCs [25, 77], and members should have the option to enable / disable such interventions.

5.3.2 Additional Information for Support-Providers to Offer In-Need Help. Our findings indicate that support-seekers' community knowledge would negatively moderate the effectiveness of received IS or ES and that if the social support in the comment matches what people seek, the support-seekers would be more satisfied. OMHCs can consider presenting such information to support-providers when they are drafting their comments, which is an emerging means to deal with ineffective or even harmful comments in OMHCs [38, 49]. For example, OMHCs can adopt machine learning models to assess the types of sought (e.g., our models for classifying sought IS and ES in Table 2) and received support (e.g., models in [56]) and present them in the sidebar when providers are drafting their comments. In addition, OMHCs can try to display support-seekers' community knowledge to the providers, e.g., ratings in the forms of stars from 1 (a small amount) to 5 (a large amount), and recommend the type of support that they may appreciate more by showing successful examples [56] or prompting associated therapeutic techniques [50]. However, OMHCs should not force commenters to change their messages if they do not feel like to since it may silence them [7].

5.3.3 Notification for Human Moderators of Dissatisfying Comments. Human moderators are responsible for keeping the extremely negative and hateful content out of the community to safeguard the environment and members [15, 73]. For example, in the MeeTwo app [44] for anonymous mental health support, all comments are checked by one of trained moderators in the app before they are released. To reduce human moderators' workload, many researchers and communities have developed various content-detection algorithms to replace or assist moderators [14, 15, 20]. The satisfaction model that we develop based on the reply's linguistic features can also serve as one tool to identify potential damage caused by bad actors. For example, when a support-seeker's reply to others is flagged as "completely dissatisfied", it is possible that someone may have said something irritating, and the human moderators could be notified to take a look. However, researchers should further examine the potential correlation and difference between support-seekers' expressed satisfaction and politeness so as not to mistakenly flag an impolite but satisfying comment [25]. OMHCs and human moderators can set a threshold for dissatisfaction to balance the workload and accuracy of identifying unsupportive members. For OMHCs like MeeTwo [44] that requires a large amount of qualified mental health caregivers, our satisfaction model can also be used to train these caregivers. For example, the communities can create virtual help-seeking posts as an exercise and use our model to score the performance of caregivers.

5.4 Limitations and Future Work

Our work has several limitations. First, this research is correlational. We use panel data and lagged dependent variables to study how support-seekers' community knowledge, sought and received support predict their reply behaviors to and expressed satisfaction with the received comment. Although this type of analysis can mitigate many problems in inferring causation from correlational data [33], we can not show that our results reflect causality between our independent variables and the reply behaviors or expressed satisfaction without true random-assignment experiments. Second, we quantitatively found that when receiving certain types of support, the members with various community knowledge express a different amount of satisfaction to the received comments, but the cause of such differences remains unclear in OMHCs. Moreover, while our statistical analyses can answer whether and how the seekers' community knowledge, sought and received support would positively or negatively affect their reply behaviors and expressed satisfaction in an OMHC for depression, the statistical significance in our findings can not stand for practical significance [40]. To learn how exactly and why these factors make a difference in practice, follow-up work can be a qualitative interview asking members how they view and react to the received comments as they stay longer and create more posts in the community.

Third, we do not control the thread structure for our regression analyses on seekers' reply behaviors and expressed satisfaction. While previous works (e.g., [70, 77]) limit the analyses on the first received comment and the corresponding seekers' reply to avoid the complexity of the thread structure, we do not restrict the position of the comment and reply since we are interested in studying seekers' satisfaction with each comment. We acknowledge that the accumulated support of previous comments in the thread might affect support-seekers' views on the incoming one [58, 66]. Fourth, as our primarily focused predictors are support-seekers' community knowledge, sought and received support, we treat other factors such as anonymity [2, 4], gender, and culture [58] of the members as random factors. Fifth, we only measure the levels of sought/received IS and ES in the posts/comments [67, 72], while there are other dimensions that can reveal subtle needs and information in the messages, such as self-disclosure [70, 75] and receiving esteem support [3, 5, 17]. Also, we estimate support-seekers' community knowledge in terms of their tenure in and posting experience in that community [67], and there could be other indicators (e.g., shared key terms [31]) of community knowledge. We suggest that future work can complement our results with greater availability of labeled data in more dimensions.

6 CONCLUSION

In this paper, we developed a machine learning model to assess support-seekers' expressed satisfaction with each received comment and systematically examined how it can be affected by seekers' community knowledge, sought and received support in an online mental health community (OMHC) for depression. We found that seekers with lower tenure or less posting experience were more likely to express satisfaction in their replies to the received comments. More specifically, when receiving ES, more experienced seekers would be less likely to convey satisfaction to the providers than those who have created fewer posts and comments before. Compared to newcomers, members who have stayed longer in the community tend to convey less contentment in their replies to the comments that contain IS. Our work adds the understanding of the relationship between support-seekers' community knowledge and their communicating of satisfaction with the comments, and we contribute a model for assessing satisfaction expressed in seekers' replies to other members of OMHCs.

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