Expression in an Online Support Forum

Machine Learning, Communication Style, and Recovery Trajectories

Ellie Yang[1]

Rachel Kornfield[2]

Yan Liu[3]

Ming-Yuan Chi[4]

University of Kentucky

Prathusha Sarma[5]

Apple Inc.

Dhavan Shah[1]

David Gustafson[1]

1, University of Wisconsin-Madison

2, Northwestern University

3, Shanghai University

4, University of Kentucky

5, Apple Inc.

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Abstract

Smartphone-based health systems are increasingly used to support behavior change and prevent relapse among substance use disorders. These systems also collect a wealth of data from participants, including the content of messages exchanged in peer-to-peer support forums. To better understand the relationship between how individuals communicate with their peers online and their recovery outcomes, the present study used supervised machine learning based on a content codebook and applied it to thousands of peer-to-peer messages exchanged over six months within a recovery app. Regression analyses examined how expression styles were associated with recovery outcomes measured on a survey at six months while controlling for these outcomes at baseline. We found, first, that our supervised machine learning approach allowed for large-scale content-coding while retaining a high level of accuracy. Second, we learned how individuals' communication styles with their online peers can help differentiate those who go on to have more positive and negative recovery trajectories. Specifically, more messages conveying emotional support predicted reduced risky drinking behaviors; more messages expressing universality - feelings of oneness of closeness to the group - predicted perceived physical health and improved quality of life; whereas more messages relaying negative affect expression negatively related to health improvement. We also found that rates of expressing emotional support and universality increased over time. This study contributes to understanding the potential ways that peer-to-peer communication can aid in recovery and highlights a method of computer-assisted content analysis that has potential application for performing large-scale content analyses in a wide array of online discussion contexts.

Key Words: Supervised Machine Learning, Online Peer Support Forum, Expression Effects, Content Analysis, Substance Use Disorder

Many digital health interventions operate by connecting individuals to supportive networks of peers who share their health status, facilitating ongoing communication through mobile, text-based messaging. Recently, smartphone-based systems have also been widely applied in the context of substance use disorders (SUDs) (Gustafson et al., 2014; Quanbeck et al., 2018) and mental health support in the COVID-19 crisis (Wind et al., 2020). Given that SUDs are serious and stigmatized conditions, bolstering peer-to-peer communication can play a crucial role for this population, offering an accessible and comfortable social context within which to discuss challenges, give and receive social support, and counteract stigma by building a positive social identity around recovery (Boisvert, Martin, Grosek, & Clarie, 2008; Farvolden, Cunningham, & Selby, 2009; Green-Hamann, Campbell Eichhorn, & Sherblom, 2011). Smartphone-based health applications (or health apps) can also unobtrusively collect a wealth of data from participants, including the content of messages exchanged. These data offer opportunities to clarify the relationship between styles of communication and participants' recovery outcomes.

The idea of connecting patient' expression styles to the recovery outcomes predates the emergence of app-based communication, For example, prior work has applied content analysis to therapists' interactions with patients in recovery for SUDs, finding that certain utterance, such as relaying one's motivations of change, precedes reduced substance use (Aharonovich et al., 2008). Digital peer-to-peer support now provides a wealth of communication data that can be used to understand how individual are faring in recovery. Unlike communication during clinic visits, this data reflects individuals' informal posts across contexts and time, potentially capturing a wide range thoughts and feelings relevant to the writer's status and recovery course. Furthermore, communicating with peers is an activity that individuals engage in voluntarily, and thus examining online communication can offer insights without additional user burden. A few recent studies have sought to examine the ways individuals communicate with their online peers in recovery, including through machine learning approaches (Ashford, et al., 2020). However, few studies have merged online communication data with patients' health and behavioral outcomes in order to understand the roles that different forms of online peer-to-peer communication might play in recovery.

This study applies such an automated content analysis approach, based on supervised machine learning, in order to examine how people communicate in a peer-to-peer mobile forum designed to support SUD recovery, and how different expression styles are related to health outcomes. This forum was a service provided in a comprehensive smartphone-based intervention designed to support SUD recovery of patients in a primary care setting. Past work has shown that social support forums for SUDs often feature disclosure of personal experiences and emotions, as well as the exchange of social support (Liu, 2017). However, individuals may have very different approaches to communicating on peer-to-peer support forums, with some largely expressing their personal thoughts and concerns, and seeking social support, while others primarily give that support to others. Furthermore, different forms of expression (e.g., sharing negative emotions versus sharing insights) and of social support (e.g., emotional vs. informational) may correspond differently to individuals' recovery process. For example, a number of studies suggest the value of giving social support as a satisfying way to engage a community of peers, build a sense of connecting, and feel needed. However, there can also be challenges in giving certain types of support, such as expressing informational support, to appropriately match to a recipient's specific recovery needs (Liu et al., 2020). To understand, in a nuanced way, how peer-to-peer communication may play a role in recovery, this paper developed a codebook for a variety of forms of expression that may bear on recovery and then hand-coded a training set to be used in supervised machine learning to "scale up" this coding to 6 months of text data. The opportunity to detect expression styles corresponding to individuals' positive or negative health trajectories may allow designers of digital interventions to intervene in more efficient and personalized ways across the recovery course.

Literature Review

The benefits of online peer-to-peer support forum for SUDs

Since 2017, an estimated 19.7 million individuals have a substance user disorder (SUD) in their lifetime, yet few of these individuals will receive SUD treatment (Substance Abuse and Mental Health Services Administration, 2018). Furthermore, SUDs outcomes are often poor even amongst patients receiving treatment, more than two-thirds returning to use of substances within months of leaving treatment (Chih et al., 2014; McLellan, Lewis, O'Brien, & Kleber, 2000; Paliwal, Hyman, & Sinha, 2008). To sustain recovery efforts and prevent relapse, Internet-based peer-to-peer support services are now increasingly applied (Gustafson et al., 2014; Kornfield et al., 2017; Liu et al., 2020). Online peer-to-peer support forums are beneficial for SUD patients for two reasons: 1) the asynchronous and anonymous communication nature of the platform and 2) the beneficial effects of expression for support solicitation and provision.

Asynchronism means the manner that online peer support forum stored "thread" initiated by a user and archived messages for others' browsing or replying not in the same time window, yet without diminishing the perceived reality of the shared experiences among participants (Walther et al., 2005; Tanis, 2008). With certain expectations about the audience in mind, individuals shift their identities through online self-presentation that may engage greater cognitive resources or achieve greater psychological growth (Gonzales & Hancock, 2008; Kornfield & Toma, 2020). Asynchronous features are convenient for users so they can engage in opportunistic browsing or posting without the time and space constraints inherent in face-to-face interactions (Abeele, De Wolf, & Ling, 2018). In addition, the anonymity of peer support groups creates a comfortable space for discussion of sensitive issues (Green-Hamann, Campbell & Sherblom, 2011; Wright, 2002). These factors create a context within which individuals are inclined to express themselves relatively freely. Both asynchronism and anonymity empower a sense of personal control that may benefit disease management, such as SUD recovery.

Apart from asynchronism and anonymity that provides an easy way to share their thoughts, issues and support with each other , users' expression behaviors in the communication process will induce possible beneficial effects for their recovery progress. Expression is defined as the "mental processes underlying the composition of language, the commitment associated with articulating ideas and creating content, and the anticipation of accountability" (Shah, 2016, p. 13). In the context of online peer support, expression is the language production for providing and receiving support in a networked communication space. Numerous studies found that expression through language production benefits disease management (e.g., Shaw et al., 2006). Patients with less offline social support tended to seek more interactions in the public forum (Kang, 2017).

One reason why expression is beneficial for health lies in the assumption that inhibitive thoughts hindering expression may associate with health risks related to early death (Pennebaker, 1997). By expressive writing, patients can release their inhibitive thoughts into beneficial cognitive and emotional processing (Greenberg & Lepore, 2004). Frattaroli (2006) found that expression training benefits mental health and physiological functioning (e.g., blood pressure). Moreover, langue use through expressive writing reflects individuals' underlying psychological states of emotion, cognition, and behavioral intention (Shim, Cappella, & Han, 2011; Tausczik & Pennebaker, 2010; Chung & Pennebaker, 2007; Cohn, Mehl, & Pennebaker, 2004; Pennebaker & King, 1999; MacReady et al., 2011; Radcliffe et al., 2007). The linguistic features help the patient connect with others for social bonding and exchange mutual support for substance abuse recovery that support psychological and physical health (e.g., Frattaroli, 2006; Coulson, 2014).

Effects of varying expression types

Though expression through online peer support forums has a beneficial effect for SUD recovery, it remains unclear what types of expression associate with health benefits. Based on previous research, expressing emotional and informational support are the two most studied types of communication in peer support contexts (Cutrona & Russell, 1990; Mo & Coulson, 2008). However, other types of expression may also contribute to positive or negative impacts. Language use in expression not only reflects psychological states, but also varies according to the patients' experiences. Relapse suffers may experience distinct emotional and cognitive patterns compared to others who are unlikely to relapse. The present study sort out seven expression types suggested relating to chronic condition management. Hypotheses are proposed to distinguish subtle effects among these seven expression types.

In an online forum, emotional support is the most common expressive type exchanged among the patients (Wright, 2002; Preece & Ghozati, 2001; Finn, 1999). Emotional support refers to messages that arouse the recipients' perceptions to be understood, respected, or loved (Yan et al., 2017). Expressing emotional support often involves empathy from the message senders, and providing emotional support is beneficial for building relationships and energizes the providers in a recovery context. For SUD patients engaged with the online forum, we expect the volume of emotional expression support would lead to positive outcomes.

H1: The more SUD patients express emotional support in the online peer support forum, the less likely they will relapse for substance use (i.e., risky drinking and drug use) and the more health benefits (i.e., mood management, perceived physical health and quality of life) they will experience.

Following emotional support, informational support is the mostly expressed in online support communities (Wright, 2002). Informational support refers to suggestions or information to help the recipients understand their world and guide his/her change in recovery activities (Tracy et al., 2010). For SUD recovery patients, informational support appears as content related to treatment, coping skills, and legal sources that provide solutions to day-to-day recovery activities (Chuang & Yang, 2014; Tracy et al., 2010). Expressing informational support facilitated message senders' self-reflection and offered a chance to reappraise one's problem (Coursaris & Liu, 2009). Evidence suggests that alcohol dependency patients who helped others with information support reduced relapse likelihood (Johnson et al., 2018; Pagano et al., 2004). But few examined the beneficial effects of informational support when controlling other types of expression.

H2: The more SUD patients express informational support in the online peer support forum, the less likely they will relapse for substance use (i.e., risky drinking and drug use) and the more health benefits (i.e., mood management, perceived physical health and quality of life) they will experience.

A third subtle expression type is negative affect. People living with chronic conditions are more likely to suffer negative emotions like depression and frustration than health populations (Kiecolt-Glaser et al., 2002), which makes them easy to suffer negative affect when seeking support. What remains controversial is whether expressing negative emotion is associated with health benefits, considering that expressing feelings facilitates emotional catharsis for psychological well-being (Donneelly & Murry, 1991). As the catharsis effect contains two stages, activation and recovery (Nichols, 1985), negative affect expression may liberate patients' feelings for future recovery. The relieving process may help SUD patients construct a sense of interpretation about his/her unconscious process that may foster cognitive change and induce new ways of reflecting on the situation and the self for therapeutic purposes. However, some studies found that negative emotion disclosure got fewer peer responsiveness (Lewallen et al., 2014; Street & Gordon, 2008), leaves a lingering stand on the effects of negative emotion expression.

RQ1: Is negative emotion expression positively or negatively associated with relapse behaviors and health benefits in SUD recovery?

Though we are not sure about the beneficial effect of negative affect expression, language containing change elements is likely to be positively associated with cognitive change. Change expression refers to “self-expressed language that is an argument for change" linked to participants' commitment to behavior change intentions (Amrhein, Miller, Yahne, Palmer, & Fulcher, 2003; Sarpavaara & Koski- Jännes, 2013). For SUD recovery, change expression is an indicator for self-controlling substance use related to positive recovery (D'Amico et al., 2015). Change expression has predominantly been examined in face-to-face therapist-client sessions but remains unclear about its function in online peer-to-peer forums. We expect a similar mechanism to be replicated online.

H3: The more SUD patients use change language in the online peer support forum, the less likely they will relapse for substance use (i.e., risky drinking and drug use) and the more health benefits (i.e., mood management, perceived physical health and quality of life) they will experience.

The fifth expression type differing itself is insight disclosure. The insightful expression produces thoughtful language to describe the stressful experience through cognitive adaption (Shim, Cappella & Han, 2011; Shaw et al., 2006). Insightful expression indicates a cognitive reappraisal process that helps individuals think about their stressors from new perspectives and reflect the cognitive function focused on self-control (Pennebaker et al., 2003). The sign of insightful thinking has been connected with individuals' adjustment for traumatic events and has been found to improve the quality of life among breast cancer patients (Shaw et al., 2006), and those recovering from anorexia (Lyons, Mehl, & Pennebaker, 2006). Yet, we do not have sufficient evidence for its beneficial role in the SUD recovery context.

H4: The more SUD patients use insightful language in the online peer support forum, the less likely they will relapse for substance use (i.e., risky drinking and drug use) and the more health benefits (i.e., mood management, perceived physical health and quality of life) they will experience.

Another common expression type is gratitude. Gratitude expression is a way to show thankfulness or appreciation towards a helper (DeSteno et al., 2010; Bartlett et al., 2012). Gratitude expression facilitates the creation of new relationships ("finding"), reinforces existing connection ("reminding"), and maintains an investment in older relationships ("binding") (Algoe, 2012; Williams & Bartlett, 2015). In social interactions, gratitude expression increases interpersonal warmth and motivation to cooperate (Cuddy, Fiske, & Glick, 2008; Cuddy, Fiske,

& Glick, 2008). Two motivational mechanisms, the agentic and communal perspectives, were proposed to explain why gratitude expression enhances personal well-being through inter and intrapersonal conditions(Grant & Gino, 2010). Some mobile health intervention programs introduced promoting gratitude expression for health benefits (Ghandeharioun et al., 2016). It is reasonable to deduce that gratitude expression be relevant and helpful in SUD recovery.

H5: The more SUD patients express gratitude in the online peer support forum, the less likely they will relapse for substance use (i.e., risky drinking and drug use) and the more health benefits (i.e., mood management, perceived physical health and quality of life) they will experience.

The last type of expression is universality. Universality is “expressing the idea that people have the same experiences or report similar experiences, circumstances, or feeling; stating that the person is ‘not all alone’…” (p222, Finn, 1999). Though universality expression is not frequently studied like emotional support in computer-mediated social support research, it is the basic language pattern serving as a validation disclosure for shared identities (Malik & Coulson; Winzelberg, 1997; Braithewaite et al., 1999). One function of the online peer support groups is to promote a feeling of universality (D’Agostino et al., 2017). However, prior research has not assessed the relation of universality with health benefits.

H6: The more SUD patients express universality in the online peer support forum, the less likely they will report substance use relapse (i.e., risky drinking and drug use) and the more they will report benefits (i.e., mood management, perceived physical health, and quality of life).

Methods

Data was collected from a smartphone-based health app that provides peer support for patients with SUDs. In a clinical trial, this app proved efficacious in reducing the likelihood of relapse (Anonymous for review). The app offers various informational and communications functions, including motivational journal writings, private messaging, games and relaxion activities, meetings and event directories, and a peer-to-peer discussion forum. The present study only draws on text data from the peer-to-peer forum, which allows members to initiate threads and to read and reply to others' posts. Messages were downloaded and then merged with each subject's survey response at baseline and after six-months, using the unique patient identifier. Over six months of using the forums, 227 participants posted 10, 548 messages in total. We focus here on 216 (95%) participants who posted at least one message in the coded content categories. The study was approved by Institutional Review Board at the authors' institution and at the study sites.

Patients over 18 years with SUDs diagnoses were recruited from three Federally Qualified Healthcare Centers in the United States from 2014 to 2017. After providing informed consent in English, participants received training on how to use the app, including its peer-to-peer discussion board. Two waves of survey data asking demographic characteristics and study outcomes were collected: one at the baseline (before accessing the app) and one after six months of using this app. The final dataset includes 216 patients in the baseline survey, and 180 for the six-month survey.

Measurement

Human and Machine Learning for Content Coding

This study employed supervised machine learning to conduct a large-scale quantitative content analysis based on a human-coded training set. To generate training data for supervised machine learning, human coders labeled a randomly selected subset of messages for the presence or absence of seven expression types (negative affect, gratitude, insightful disclosure, change talk, emotional support, informational support, and universality). Coders achieved satisfactory inter-rater reliability for each category (Cohen's kappa >.7). Table 2 displays the operationalization of the seven communication types, example messages, and inter-rater reliability among human coders. Codes were not mutually exclusive, meaning that the same message could include multiple communication types.

(Insert Table 1 here)

Drawing on prior work (Kornfield et al., 2018), we next extracted linguistic features from the full set of messages using the Linguistic Inquiry and Word Count (LIWC) program, with LIWC's approximately 90 linguistic dimensions used as features in boosted decision tree models that were applied to classify the full dataset based on the labeled data, with results assessed via ten-fold cross-validation (Witten, Frank, Hall, & Pal, 2016). For content categories with imbalanced classes (e.g., far more messages did not mention gratitude than did), we compensated for this imbalance by oversampling from the minority class using the Synthetic Minority Oversampling Technique (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). We employed scikit-learn in Python to calibrate the classifier in this study. Table 2 presents the algorithm performance indexes for the coded messages.

(Table 2 inserts here)

Survey measures

Relapse-related variables (i.e., risky drinking and drug use) and other health outcomes (i.e., quality of life, mood management, depression) were self-reported through surveys administered at baseline and 6-month follow-up.

Risky Drinking Behavior. The survey asked the patients to recall in the past 30-days "whether you have reached or exceeded the threshold of binge drinking" at baseline and the end of

6month. The binge drinking threshold was defined as consuming more than three drinks for women or more than four drinks for men within 2 hours (Center for Behavioral Health Statistics and Quality, 2018).

Drug Use Behavior. The survey asked the patients "whether you have used any illegal/street drugs or abuse any prescription medications in the past 30 days".

Mood Management. Positive and Negative Syndrome Scale (PANAS) was deployed to measure mood management. The PANAS scale consists of 20 items in which the 10 measures positive affect and the other 10 for negative affect (Watson, Clark, & Tellengen, 1988).

Physical Health. Four items about general physical health, physical activities such as walking, climbing stairs, carrying groceries, or moving a chair, fatigue, perceived pain were asked on a five-point and ten-point scale (Hays, et al., 2017). Mean of each item were aggregated to represent the physical health score.

Quality of Life. PROMIS Global Health Scale (Hays et al., 2009) was used to measure the perception of the quality of life. The scale consists of 10 items that assess overall physical health and mental health.

Analytical Strategy

After receiving the two-wave surveys and having content-coding finished, the researcher integrated machine-classified data with baseline and the 6-month follow-up survey data based on user IDs. The count of each expression type was aggregated per user over the six months. To control the heterogeneous influence from patients' uneven message production, we created a proportion score for each expression type that used the raw count per type per user divided the sum of posts each patient wrote. In other words, we applied the percent of expression types instead of raw count in the model estimation. Hierarchical OLS and logistic regressions were used to assess how the proportion of an individual's expression types predicted the five health outcomes. All models controlled for participants' baseline health measurement and gender, age, education, and race. SPSS (ver. 25) was employed for the regressions. To capture each expression type's change rates, we also used Mplus (ver. 8) for latent growth curve models as a supplementary analysis in the appendix.

Results

Descriptive Results

Table 3 presents the change of demographic features and outcome measurement from the two-wave surveys. A total of 10, 503 messages among 216 users were posted on the peer-to-peer support board. Patients had more frequent activities in the first four months; almost 83% of messages were produced during that time window. Figure 1 presents the sum of messages per month. In the 10, 503 messages posted in the six-month period, emotional support was the most common expression type (4788, 45.6%), followed by gratitude expression (2972, 28.3%), informational support (2514, 23.9%), and the least common expression type is change expression (707, 76.7%).

(Insert Table 3 here)

(Insert Figure 1 here)

Table 4 displays the average proportion for each expression type and the count of users who expressed the corresponding category for the monthly change. The left column under each month suggests that emotional support was mostly expressed from the first to the sixth month, with a slight increase since the third month. Other types of expression also had a slight increase in the middle of the study period. Regarding how many users expressed every month, it is apparent that the absolute number of user count for each expression type was decreasing.

However, the relative proportion of users expressing emotional support was increasing. The descriptive results in table 4 imply a relative growth of emotional support expression for both expression proportion score and user count. There was also a slight increase in the proportional score for expression types like universality, negative emotion, informational support, general change, and insight disclosure. To verify whether such an increasing trend at monthly intervals is significant or not, we supplemented a latent growth model specializing in estimating growth trajectories as an additional analysis in the appendix.

(Table 4 inserts here)

Hypotheses Testing

A series of hierarchy OLS and logistic regressions were employed to predict risky drinking, drug use, mood, perceived physical health, and quality of life. Significant results suggest that specific expression effects are associated with risky drinking, mood, and life quality. Health benefits like abstinence drug use could not be achieved through expressive writings in online peer support.

For the risky drinking behaviors, Table 5 shows that expressing more emotional support was significantly associated decreasing risky drinking; averagely speaking, increasing one proportion of emotional support will bring about 9% possibilities to have less risky drinking days. In contrast, informational support was positively related to increased risky drinking.

(Insert Table 5 here)

We found that expressing negative emotion significantly decreased positive mood at 6 month (Table 6). Similar results occur to perceived physical health (Table 7) and improving quality of life (Table 8). One more proportion of increasing negative expression would decrease the score of physical health fourfold (Table 7) and decrease quality of life perceptions (Table 8).

However, universality expression was found to be beneficial in improving physical health to a large amount ($\beta = 6.392$, $p < .001$), as well as enhancing the quality of life ($\beta = 12.069$, $p < .005$). In conclusion, among the seven expression types across different health outcomes, emotional support and universality have buffer effects when controlling the covariates. Parts of H1 and H5 are supported. H2, H3, and H4 are not bolstered in this study. Negative affect expression had no positive impact across health measurement, suggesting its harmful role in SUD recovery. RQ1 is addressed. Our results did not find informational support expression that may be in line with prior research about its relatively limited role in tackling loneliness feelings in SUD recovery (Perry & Pescosolido, 2015).

Supplementary Analysis

Table 1 in the appendix suggests that there was a growing rate for emotional support every month, for the increasing slope change ($\beta = .012$, $p < .05$) is significant with a good model fit (CFI = .906, SRMR = .072, BIC = 527). Another latent growing expression category is universality ($\beta = .008$, $p < .01$), indicating that the next month had a 0.8% increasing rate among people who have expressed universality discourse. Yet, the model fit for universality expression is not good as emotional support (CFI = .568, SRMR = .118, BIC = -735). A conditional latent growth model was also applied to investigate what demographic covariates influenced the expression intercepts and slopes. Table 2 in the supplementary analysis reveals that patients with old age had a latent growth rate for emotional support ($\beta = .001$, $p < .05$), and patients with higher education background had a decreasing slope in each month ($\beta = -.004$, $p < .05$). As for the intercepts change, all the demographics had more or less impact on the monthly initial state for several expression types except for risking drinking days at the baseline.

Discussion

Peer-to-peer discussion within SUDs apps can provide a wealth of data about individuals' health trajectories, but the time required for hand review and coding of messages for psychological constructs can quickly become prohibitive. This paper demonstrates that unobtrusive assessment through automated content analysis may offer opportunities to test theories regarding health behavior change and potentially tailor digital interventions in real-time to better respond to participants' recovery trajectories. Using the fusion of human coding, off-the-shelf language processing software (LIWC), and supervised machine learning algorithms, we successfully performed a large-scale content analysis with a level of accuracy that approximated the judgment of a human coder. Our results add to a growing body of evidence suggesting that informal online conversations may be a valuable source of information about participants' future health trajectories (De Choudhury, Counts, & Horvitz, 2013; Eichstaedt et al., 2018).

In particular, our content analysis results suggest that giving social support, particularly emotional support, was the primary use of this peer-to-peer forum, consistent with prior research based on a hand labeling approach (Chuang & Yang, 2011; Liu et al., 2017). Expressing emotional support is also beneficial to prevent risky drinking relapse. Our findings are consistent with prior research highlighting negative affect as a significant predictor of health risks (Kornfield et al., 2017). Universality expression, wherein individuals recognize their commonality with other group members, has a beneficial effect for depression release and improving quality of life, which may beneficial for addiction treatment. These findings have practical significance for the design of online forums since groups could be composed to enhance universality, such as by bringing together more similar members.

Moreover, the supplementary analysis reveals that the longer patients engaged with this online support forum, the greater growth rate of emotional support and universality they had. For emotional support, female and non-Caucasian patients were more likely to express themselves over time. As for the growth of universality expression proportion, older and female users were less likely to disclose longitudinally. Such results indicate that different demographic subgroups may benefit from differential expression effects for recovery support when engaged with online peer-to-peer forums together. This hybrid approach will aid scalability to optimize health intervention effectiveness and efficiency beyond clinical trial. With the prevalence of the Internet, online peer-to-peer forums represent a growing recovery support venue.

Our study also contributes to answer which types of online expression may have a beneficial effects for SUD recovery. Different from previous research, this study distinguished varying expression types in an online peer support forum, which advances previous journal writing as a major method to detect expression effects for psychological well-being. However, expression online may not be beneficial for every participant as there were more lurkers (i.e., who participate without posting) in online forums (Setoyama et al., 2011). Forum designers need to maximize the health benefits among lurkers and think of ways to alleviate the common "cold-start problems" and motivate more participants to interact. The second issue is to stimulate beneficial expression for specific subgroups. Our results imply that not all expression types are positively related to health benefits and demographics impacted expression volume. These results will become compound when we integrate other personal dispositions such as self-efficacy. One study found that the beneficial effects of emotional disclosure were moderated by our self-efficacy abilities (Liu, 2017). It is worthwhile noting the two questions in mind when considering therapeutic expression strategies in preventing SUD relapse programs.

In addition to motivate therapeutic expression in online forums, researchers in SUD recovery programs should consider strategies to help patients reduce negative affect expression. It is not only that negative emotional expression had no beneficial effects for any health outcomes, but prior research also supports that negative emotional disclosure received far less online support (Liu, 2017). Though we are unsure whether disclosing vulnerabilities still have a catharsis effect in converse-U shape, negative affect expression lasting six months is not a positive sign for health recovery.

The study has two significant limitations. The first one is that we did not distinguish expression types among support seekers and providers. Future research may differ in messages as support requests and support provision before coding them into the expression category. A second limitation is that our sample was not randomly collected, so the conclusion lacks generalizability. Further studies can recruit users representative of population characteristics at structural levels such as residential communities. It may be a deficit in the present research that we did not require the patients to write on the app, so the result may not be held for users never posted. However, our research extends prior emphasis on emotional and informational support expression to other types of langue production largely ignored by previous online forum studies. Namely, we found the opposite role of negative affect and universality expression effects for SUD recovery. These findings will pave the way for online peer support forum research to access recovery-relevant language elements in the future.

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Figure 1. Count of Messages Monthly

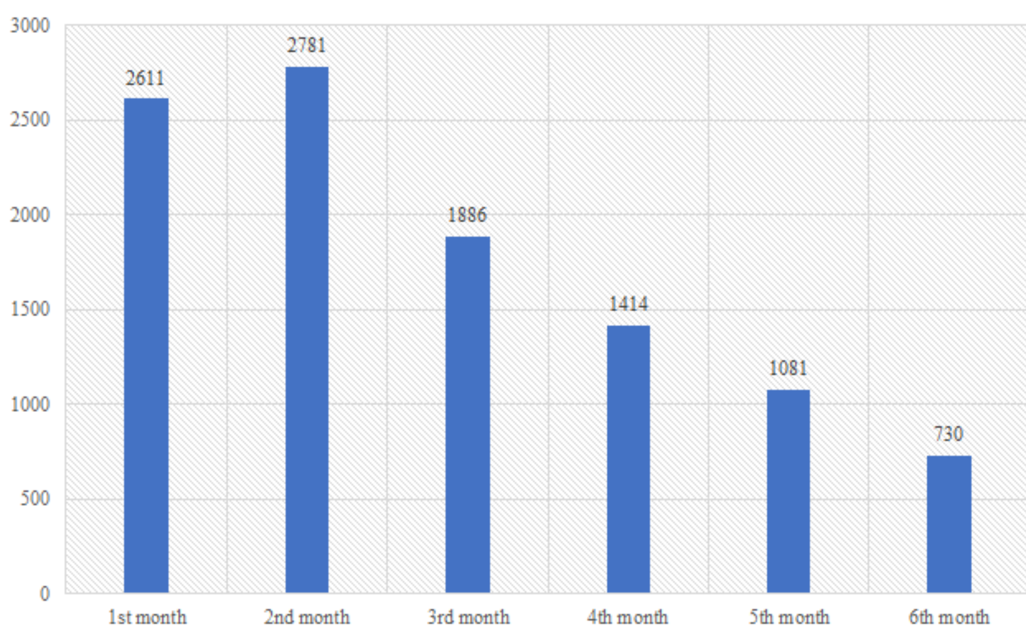

Table 1. Operationalization, Example Messages and Inter-rater Reliabilities for the Seven Expression Types

Expression Types	Operationalization	Example Message	Cohen's Kappa (human coding)
Emotional Support	Messages arouse the coders emotional response to be understood, admired, respected, loved, etc.	"That's awesome you're feeling better."	0.73
Informational Support	Messages relate to knowledge, and/or advice to help the recipient understand a specific problem.	"Exercise helps for anxiety"	0.78
Universality	Messages express the recognition with certain situation or describe the same or similar feelings.	"I too Have felt the same, depressed on so many different levels."	0.72
Gratitude	Appreciation to a specific human subject or generally expressing gratitude	"Thank you" "thanks theodog60. :)"	0.94
Insight	Cognitive statements related to thinking consciously.	"I realized how important it is to take care of myself. "	0.73
Negative Affect	Messages arouse negative feelings such as frustration, sadness, anger.	"Sometimes I feel like I'm going crazy. Just needed to vent"	0.84
Change talk	Messages indicate consciousness of change or directional shift.	"I have to put down and stop alcohol and drugs"	0.70

Table 2. F-Scores, Sensitivity, and Specificity for Boosted Decision Tree Learning Algorithm Performance

Expression Types	F-score	Sensitivity	Specificity
Emotional Support	0.73	0.72	0.73
Informational Support	0.87	0.88	0.86

Universality	0.98	0.99	0.96
Gratitude	0.93	0.94	0.91
Insight	0.84	0.85	0.81
Negative Affect	0.89	0.91	0.86
Change talk	0.81	0.78	0.83

Table 3. Descriptive statistics at baseline and the 6-month

	Baseline (N = 216)		6-Month (N = 180)	
Demographics	n	%	n	%
Gender				
Male	114	52.8	94	52.2
Female	102	47.2	86	47.8
Race				
White	143	66.2	120	66.7
Non-White	73	33.8	60	33.3
Education				
Below college	108	50.0	87	48.3
Some college	64	29.6	57	31.7
Above college	44	20.3	36	20.0
Age	Mean = 41.8, SD = 10.60		Mean = 42.3, SD = 10.73	
	Baseline (N = 216)		6-Month (N = 180)	
Outcomes	n	%	n	%
Risk drinking (=Yes)	68	31.5	40	18.5
Drug use (=Yes)	60	27.8	27	12.5
Mood management	Mean = 3.22, SD = .76		Mean = 3.54, SD = .71	
Depression	Mean = 10.19, SD = 5.72		Mean = 7.69, SD = 5.58	
Quality of life	Mean = 28.48, SD = 9.70		Mean = 30.02, SD = 7.02	

Table 4. Average proportion score per user and user count of the seven expression types

	1st Month (N=216)		2nd Month (N=190)		3rd Month (N=163)		4th Month (N=136)		5th Month (N=115)		6th Month (N=97)	
	Average proportion	user count	Average proportion	user count	Average proportion	user count	Average proportion	user count	Average proportion	user count	Average proportion	user count
emotional support	.40 (.31)	167 (77%)	.40 (.32)	141 (74 %)	.47 (.34)	129 (79%)	.45 (.35)	103 (76%)	.48 (.33)	95 (83%)	.44 (.33)	78 (80 %)
universality	.06 (.12)	81 (38%)	.09 (.18)	77 (41%)	.07 (.13)	62 (38%)	.09 (.17)	50 (37%)	.12 (.22)	48 (42%)	.11 (.22)	37 (38 %)
negative emotion	.06 (.12)	74 (34%)	.09 (.17)	79 (42%)	.08 (.18)	56 (34%)	.08 (.17)	43 (32%)	.11 (.22)	45 (39%)	.07 (.18)	30 (31%)
informational support	.20 (.26)	129 (60%)	.25 (.28)	124 (65%)	.22 (.26)	93 (57%)	.25 (.28)	84 (62%)	.25 (.29)	68 (59%)	.26 (.30)	59 (61%)
general change	.07 (.17)	80 (37 %)	.07 (.17)	70 (37%)	.06 (.16)	50 (31%)	.08 (.17)	45 (33%)	.11 (.20)	49 (43%)	.08 (.18)	33 (34%)
gratitude	.26 (.24)	158 (73%)	.25 (.25)	130 (68%)	.27 (.29)	109 (67%)	.28 (.31)	87 (64%)	.27 (.28)	74 (64 %)	.25 (.29)	59 (61%)
insight disclosure	.14 (.21)	108 (50%)	.18 (.27)	104 (55%)	.19 (.26)	93 (57%)	.18 (.24)	70 (52%)	.18 (.27)	59 (51%)	.15 (.21)	44 (45 %)

Note. Standard deviation in the parentheses.

Table 5. Hierarchy logistic regression models using expression types to predict whether to have risky drinking by the end of the sixth month.

	Model 1		Model 2	
	Estimate	OR	Estimate	OR
Demographic				
Age	-.04+	.96	-.04+	.96
Education (Ordinal Scale)	.07	1.07	.11	1.12
Male	.31	1.37	.14	1.15
White race	-.62	.54	-.74	.48
Risky drinking control	2.27***	9.69	2.42***	11.21
Expression Types				
Emotional support			-2.40*	.09*
Informational support			2.90*	18.21*
Universality			-.14	.87
Negative emotion			-.04	.96
General change			-5.34	.005
Gratitude			1.56	4.74
Insight disclosure			-.53	.59
(Intercept)	-.50	.61	-.06	.95
Log Likelihood	148.28		139.94	

Note. OR = odds ratio. *$*p < .05$ $**p < .01$ $***p < .001$*

Table 6. Hierarchy regression models using expression types to predict mood management by month six.

	Model 1	Model 2	Model 3
Demographic			
Age	.3.991E	-.008+	-.009*
Education	-.010	-.086	-.064
Male	.227	.139	.122
White race	-.048	-.080	-.073
Risky drinking control	-.227*	-.050	-.014
Baseline control			
Mood		.551***	.559***
Expression types			
Emotional support			-.115
Informational support			-.115
Universality			-.138

Negative emotion			-1.453**
General change			.826
Gratitude			-.004
Insight disclosure			.233
(Intercept)	3.605***	2.152***	2.256***
R square	.047	.341	.374

Notes. Standardized coefficient estimates are reported.
$^{+}p < .01$ $*p < .05$ $**p < .01$ $***p < .001$

Table 7. Hierarchy regression models using expression types to predict self-reported physical health by month six.

	Model 1	Model 2	Model 3
Demographic			
Age	-.105***	-.075***	-.081***
Education	.801+	.792*	.997**
Male	.970*	.692+	.658+
White race	.373	.309	.214
Risky drinking control	-1.177*	-.476	-.602
Baseline control			
Physical health		.506***	.499***
Expression types			
Emotional support			.758
Informational support			-.854
Universality			6.392**
Negative emotion			-4.942*
General change			-2.935
Gratitude			-1.902
Insight disclosure			.100
(Intercept)	17.074***	9.090***	9.869***
R square	.167	.386	.447

Notes. Standardized coefficient estimates are reported.
$^{+}p < .01$ $*p < .05$ $**p < .01$ $***p < .001$

Table 8. Hierarchy regression models using expression types to predict quality of life by month six.

	Model 1	Model 2	Model 3
Demographic			
Age	-.145**	-.114*	-.127**
Education	1.231	.972	1.407
Male	1.565	1.480	1.501
White race	1.582	1.279	1.341
Risky drinking control	-2.368*	-.650	-.765
Baseline control			
Global health		.573***	.577***
Expression types			
Emotional support			.384
Informational support			-2.081
Universality			12.069*
Negative emotion			-10.649*
General change			-2.664
Gratitude			-1.147
Insight disclosure			-1.507
(Intercept)	34.407***	16.575***	17.721***
R square	.092	.348	.385

Notes. Standardized coefficient estimates are reported.
*+p < .01 *p < .05 **p < .01 ***p < .001*

Supplementary Analysis

Table 1. Unconditional latent growth model regression estimates for expression types

	Intercept		Slope		CFI	SRMR	BIC
	Est.	SE	Est.	SE			
Emotional Support	.394***	.017	.012*	.005	.906	.072	527
Information Support	.215***	.015	.008	.006	1	.071	250
Universality	.062***	.007	.008**	.003	.568	.118	-735
Negative Emotion	.067***	.008	.003	.004	1	.085	-744
General Change	.065***	.008	.005	.004	.669	.089	-604
Gratitude	.262***	.014	.000	.005	.849	.092	222
Insight Disclosure	.152***	.015	.006	.005	.812	.090	-25.7

Notes. $^{*}p < .05$, $^{**}p < .005$, $^{***}p < .001$

Table 2. Conditional latent growth model for monthly expression change and OLS for overall expression score by month six

	Intercept		Slope		CFI	SRMR	BIC	Overall	
	Est.	SE	Est.	SE				Est.	SE
Outcome: Emotional Support					.840	.069	564		
Education	.004	.013	-.002	.004				.008	.032
Age	.000	.002	.001*	.000				.002	.002
Male	-.070*	.035	.009	.011				-.045	.032
Caucasian	-.078*	.036	.007	.012				-.047	.034
Risky drinking control	.001	.037	.007	.012				.002	.034
Outcome: Information Support					.961	.068	278		
Education	.019	.011	.006	.004				.040	.028
Age	.001	.001	.001	.000				.002	.001
Male	-.014	.029	-.005	.011				-.015	.028
Caucasian	.012	.031	.013	.012				.025	.030
Risky drinking control	.005	.031	-.015	.011				-.007	.030
Outcome: Universality					.636	.098	-697		
Education	.011	.006	-.002	.002				-.006	.014
Age	-.001*	.001	.000	.000				-.001	.001
Male	-.033*	.013	.001	.006				-.035*	.014
Caucasian	.008	.012	.003	.007				.018	.014
Risky drinking control	.000	.016	-.003	.006				.009	.014
Outcome: Negative Emotion					.982	.073	-675		
Education	.013**	.005	-.004*	.002				.018	.013
Age	-.001	.001	.000	.000				-.001	.001
Male	-.032**	.013	.011	.008				-.015	.013
Caucasian	.022	.013	-.004	.006				.025	.014
Risky drinking control	-.002	.015	.010	.007				.021	.014
Outcome: General Change					1	.071	-565		
Education	.012*	.005	-.001	.002				.019	.016
Age	-.001	.001	.000	.000				-.001	.001
Male	-.027	.018	.012	.007				-.016	.016
Caucasian	.018	.017	.001	.008				.016	.017
Risky drinking control	-.029	.018	.009	.006				-.029	.017
Outcome: Gratitude					.789	.077	263		

Education	.005	.010	-.002	.004				-.014	.026
Age	-.001	.001	.001	.000				-.001	.001
Male	-.042	.028	.000	.010				-.055*	.026
Caucasian	-.064*	.031	.007	.011				-.056*	.027
Risky drinking control	.013	.029	-.011	.010				-.017	.027
Outcome: Insight Disclosure					.876	.074	6.642		
Education	.033**	.011	-.005	.003				.032	.026
Age	-.003**	.001	.000	.000				-.003*	.001
Male	-.017	.026	-.004	.008				-.047	.026
Caucasian	. 016	.027	.000	.009				.034	.028
Risky drinking control	.000	.031	.003	.010				-.01	.028

Notes. $^{*}p < .05$, $^{**}p < .005$, $^{***}p < .001$