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Application of Automated Text Analysis to Examine Emotions Expressed in Online Support Groups for Quitting Smoking

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Abstract

Online support groups offer social support and an outlet for expressing emotions when dealing with health-related challenges. This study examines whether automated text analysis of emotional expressions using Linguistic Inquiry and Word Count (LIWC) can identify emotions related to abstinence expressed in online support groups for quitting smoking, suggesting promise for offering targeted mood management to members. The emotional expressions in 1 month of posts by members of 36 online support groups were related to abstinence at month end. Using the available LIWC dictionary, posts were scored for overall positive emotions, overall negative emotions, anxiety, anger, sadness, and an upbeat emotional tone. Greater expressions of negative emotions, and specifically anxiety, related to nonabstinence, while a more upbeat emotional tone related to abstinence. The results indicate that automated text analysis can identify emotions expressed in online support groups for quitting smoking and enable targeted delivery of mood management to group members.

Quitting smoking is extremely challenging, and nicotine withdrawal causes increased negative emotions for at least 2–4 weeks after quitting (Prochaska and Benowitz 2019). Managing emotions is critical to successful smoking abstinence (Kassel, Stroud, and Paronis 2003). Online support groups for quitting smoking hosted on social media apps (e.g., Twitter, Facebook) offer both social support and an outlet for emotional expressions (Pechmann et al. 2017). Support group members regularly express their emotions organically, which may reflect their daily experience better than retrospective self-report measures of emotional states. When integrated into online support groups, automated or computerized text analysis of emotional expressions in posts may aid in targeting real-time delivery of mood management support to members in need and in providing encouragement to those who are successfully managing their mood.

As a first step to using automated text analysis to deliver targeted mood management and encouragement to online support group members, it is important to understand whether

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text analysis can identify expression of emotions relevant to the target goal (e.g., smoking abstinence). The present study tested the efficacy of the popular automated text analysis software Linguistic Inquiry and Word Count (LIWC) at scoring the emotional expressions in group members' posts. Efficacy was assessed by examining the relationships between emotional expressions and abstinence. Prior studies have mined social media posts to predict the posters' smoking status (Wang et al. 2019) and to categorize discussion topics (Burri, Baujard, and Etter 2006; Pechmann et al. 2015; Cole-Lewis et al. 2016). However, to our knowledge, this is the first study to use automated text analysis to score the emotional expressions in posts in online support groups and relate these scores to target goal attainment. We show that automated text analysis can successfully identify emotions that are associated with abstinence, indicating this may be a useful, novel approach to offering tailored real-time mood management to online support group members.

EXPRESSION AND MANAGEMENT OF EMOTIONS IN ONLINE INTERVENTIONS

Mobile health (mHealth) interventions, such as mobile apps and text messaging, are increasingly used to provide quit-smoking support (Whittaker et al. 2019). Several text message interventions address mood management. For example, Text2Quit (Abroms et al. 2012), Quit4Baby (Abroms et al. 2017), and Text to Quit China (Augustson et al. 2017) use cognitive-behavioral approaches to help users cope effectively with triggers, including negative emotions. However, it is unclear whether mood management is a key component of intervention success.

Several mobile apps enable users to track their emotions and urges to smoke. Crush the Crave (Baskerville, Struik, and Dash 2018), Quit Advisor Plus (BinDhim, McGeechan, and Trevena 2018), and MobileQuit (Danaher et al. 2019) include tracking features to assist users in identifying patterns between their emotions and their smoking. MobileQuit includes mood management features such as guidance on increasing pleasant activities, identifying and countering negative thoughts, coping with stress, and managing negative emotions (Danaher et al. 2019). Apps such as Craving to Quit (Garrison et al. 2015) and SmartQuit (Bricker et al. 2014) teach mindfulness (i.e., acknowledging and accepting momentary experience) and principles from acceptance and commitment therapy (e.g., engaging in values-aligned behaviors while experiencing emotions), which can support abstinence. However, it has not yet been established whether such apps actually help smokers quit (Whittaker et al. 2019). Moreover, apps are often limited to interactions between the user and automated features of the app, without the opportunity to discuss challenges with peers or obtain social support.

Online support groups for health-related concerns are very popular, with 14 million adult users in 2018 (National Cancer Institute 2018). Online contexts can promote emotional disclosure by increasing social connection and offering social support (Luo and Hancock 2020), and online health-related support groups can serve as safe places to express emotions related to health challenges (Mo, Malik, and Coulson 2009). Social media is an increasingly popular delivery platform for quit-smoking support groups (Thrul, Tormohlen, and Meacham 2019), with high feasibility and acceptability (Naslund et al. 2017). In contrast to text messaging and apps, which provide content with little or no social interaction, social media support groups allow individuals to share experiences, emotions, and advice with peers (Pechmann et al. 2015; Bradford, Grier, and Henderson 2017). Automated text analysis of group members' posts may yield timely and useful insights regarding emotional experiences beyond what can be captured by self-report measures, with no added participant burden, and potentially facilitate targeted real-time mood management interventions to group members who would benefit from them.

CURRENT RESEARCH

The goal of this study was to determine whether automated (computerized) text analysis could identify emotional expressions in online quit-smoking support groups that are related to smoking abstinence. Although this study could not determine whether specific emotions cause abstinence or relapse, identifying associations can still aid in understanding smoking cessation outcomes. For this study, we used 36 Tweet2Quit online support groups (Pechmann et al. 2017). A prior social network analysis of Tweet2Quit groups found that extensive communications took place among group members and that meaningful connections formed between pairs and triads of people, with a variety of thoughts and emotions expressed (Lakon et al. 2016). In the current study, which involved a completely new set of Tweet2Quit groups, group members' posts (tweets) were scored for emotional expressions using LIWC software (Pennebaker et al. 2015).

LIWC analyzes the extent to which written text (e.g., social media posting) expresses certain concepts, using a dictionary of words commonly used to express each concept. Over 100 studies have validated LIWC's automated scoring method (Tausczik and Pennebaker 2010). For instance, automated text analysis of messages in an online breast cancer support group demonstrated that emotions identified by LIWC corresponded with human coders' ratings and that LIWC accurately differentiated between news articles about breast cancer that varied in emotional content (Alpers et al. 2005). Prior research has also shown strong correlations between emotions captured by LIWC and those captured by human coders, with emotional expressions predicting subsequent health center visits (Pennebaker and Francis 1996). Hence, LIWC has considerable potential for identifying group members who might be struggling to manage their emotions. Our study tested LIWC's usage for this purpose.

LIWC's dictionaries allow for the scoring of overall positive and overall negative emotions as well as three specific negative emotions: sadness, anger, and anxiety. Specific positive emotions are not included, perhaps because positive affect tends to be more diffuse than negative affect, with this imbalance thought to be an evolutionary adaptation (Frederickson 1998). Negative emotions are action oriented, prompting responses to threat. Positive emotions, while important in building resilience, are less specific and less amenable to urgent action. This imbalance in the importance of discrete positive versus discrete negative emotions is reflected in facial expressions, autonomic responses, and the English language itself (Frederickson 1998).

We hypothesized that expressions of overall negative emotions would relate to smoking nonabstinence. Negative emotions are especially common during the early stages of abstinence and often precipitate relapse (Kassel, Stroud, and Paronis 2003; Baker et al. 2004; Shiffman and Waters 2004; Minami et al. 2017). Considering specific negative emotions, we hypothesized that expressing greater sadness (Garg and Lerner 2013; Dorison et al. 2020), anxiety (Brown et al. 2001; Zvolensky et al. 2009; Langdon et al. 2016), and anger (Patterson et al. 2008; Cougle et al. 2014) would also relate to smoking nonabstinence.

Conversely, we hypothesized that expressions of overall positive emotions would relate to abstinence. Positive emotions facilitate development of coping skills (Frederickson 1998; Samios, Abel, and Rodzik 2013; Kearney et al. 2014), enhance resilience (Cohn et al. 2009), and increase receptivity to information about health risks (Agrawal, Menon, and Aaker 2007). LIWC also scores for an upbeat emotional tone (described below), and we expected higher upbeat emotional tone scores to relate to abstinence. We did not form hypotheses regarding specific positive emotions, because LIWC does not contain dictionaries for specific positive emotions, possibly owing to positive emotions generally being more diffuse and nonspecific than negative emotions (Frederickson 1998). Also, regularly experiencing positive emotions in general, rather than any specific positive emotion, facilitates resilience (Frederickson 1998).

In sum, this study aimed to improve on existing mHealth interventions for quitting smoking by pairing features of online support groups with automated text analysis to assess group members' emotional expressions. Online support groups offer an outlet for gaining and providing social support, expressing emotions, and attaining health goals (e.g., quitting smoking). The conversational and communal nature of such groups lends itself to rich emotional expression. Given previously identified associations between negative emotions and failing to quit smoking or relapsing, interventions are especially needed to identify group members who are struggling with negative emotions. Automated text analysis may be a novel approach to intervening in online support groups with meaningful mood management strategies based on real-time emotional expressions.

METHOD

Support Groups, Participants, and Measures

Support Groups.—Tweet2Quit provided 36 private, 20-person, peer support groups for quitting smoking on Twitter. Group members were instructed to set a quit date within 10 days of group start, given a quit buddy within the group, and encouraged to post at least daily. Everyone in a group could see others' posts, but the group was closed to non-members. Consistent with clinical practice guidelines, group members were given 8 weeks of free combination nicotine replacement therapy (i.e., nicotine patches plus nicotine gum or lozenges; Fiore et al. 2008). Twitter API was used to automatically post a daily discussion topic. Many of these posts encouraged sharing of emotional experiences (e.g., "When it gets tough making a behavior change like this, what keeps you going?" and "What triggered you to smoke and how will you resist?"). In addition, each support group member was automatically sent a daily text providing feedback on their past 24-hour engagement with the group (i.e., praise for participating or encouragement to reengage). Daily texts only gave feedback on engagement with the group and did not provide any therapeutic support.

Participants.—In the parent study of which this study is a subset, 720 adult smokers, ages 21–59, were recruited for a randomized controlled trial on quitting smoking and were randomized to a coed support group, a women-only support group, or a control condition with no support group (Pechmann et al. 2020). From this parent study, 606 adult smokers were included in the present study because they met these key criteria: assignment to one of the support groups (not control) thereby providing posts that allowed for text analysis, posting to their group at least once enabling us to do our text analysis, and reporting their abstinence status at 1 month. We could not test whether emotional expressions related to abstinence among controls because they were not in support groups and hence did not provide text samples to code. Similarly, we could not test whether emotional expressions related to greater abstinence in support groups compared to controls because of the lack of textual data from controls; moreover, in the support groups, the positive and negative emotions expressed had conflicting associations with abstinence.

We recruited participants on Facebook. As in most quit-smoking interventions that provide free nicotine replacement therapy, smokers needed to report readiness to quit within the next 30 days to be eligible (Lindson et al. 2019). Participants were also screened for Facebook use to ensure familiarity with social media, valid contact information, mobile phone with free texting, and eligibility for nicotine replacement.

Measures.—Group members' posts were collected for 1 month. After their group had been active for 1 month, each group member was contacted and asked how many cigarettes they had smoked in the past week. Those reporting no past-week cigarettes were considered abstinent (Hughes et al. 2003).

Analyses

Scoring of Emotional Expressions.—LIWC scans text samples and tabulates matches between the text and the concept, creating a score for each concept (Pennebaker et al. 2015). Text samples used in the development of LIWC included Twitter posts (Pennebaker et al. 2015). Each Tweet2Quit group member received a score pertaining to each emotional category available in the LIWC dictionary, which included overall positive emotions, overall negative emotions, and the specific negative emotions of anxiety, anger, and sadness. A score for each emotion was calculated by matching the group member's posts to the LIWC's dictionary of words, which had 116 words for anxiety, 136 words for sadness, 230 words for anger, 620 words for overall positive emotions, and 744 words for overall negative emotions. A point was added to the score when a word in the post matched a word in the dictionary, such that the sum for each emotion reflected the number of words a group member used to express that emotion during the 1-month study period. For example, if a post included the word "cry," a point was added to both the "sadness" and "overall negative emotion" sums. The sum of words for each emotion was then divided by the total number of words, such that each emotional score reflected the proportion of total words that conveyed the emotion (Pennebaker et al. 2015).

LIWC also calculated each group member's score on upbeat emotional tone, which reflected the extent to which the member's posts conveyed positive upbeat emotions as compared to negative downbeat ones. Each member's score was expressed as a percentile (0–100) based on a benchmark developed from large comparison samples (Pennebaker et al. 2015). Percentile scores around 50 (40–59.99) indicate average use of positive upbeat words (e.g., happy, good, or nice) as compared to negative downbeat words (e.g., kill, ugly, or guilty). Higher percentile scores (≥ 60) indicate above average use of positive upbeat words as compared to negative downbeat ones, while lower percentile scores (< 40) indicate the opposite (Cohn, Mehl, and Pennebaker 2004).

Associations between Emotions and Abstinence.—Individual-level data were analyzed, in that each group member had scores for each of the six emotional expressions based on 1 month of Twitter posts and an abstinence score (abstinent or nonabstinent at month end). Associations between each of the six emotional expression scores and smoking abstinence were determined using separate generalized estimating equations with binary distributions and logit link functions, accounting for clustering of group members into different support groups. In each of these six models, the emotional expression score was entered as the predictor, with abstinence as the outcome. All analyses were adjusted for these covariates: participant gender (male vs. female), age, race/ethnicity (non-Hispanic White vs. other), initial cigarettes per day, and support group composition (women-only vs. coed).

RESULTS

The 606 adult smokers whose posts were analyzed were 82.1% female with a mean age of 39.43 (SD = 9.59), and 81.1% were non-Hispanic White ($n = 494$), 11.3% Black ($n = 69$), and 7.6% another race/ethnicity ($n = 46$). Most were married ($n = 243$, 39.9%) or living with a partner ($n = 119$, 19.5%). They had smoked on average 17.42 cigarettes per day (SD = 7.61) before their quit attempt. Most of the current participants ($n = 396$, 65.0%) were assigned to the 24 coed support groups; 213 (35.0%) were assigned to the 12 women-only support groups.

We analyzed 58,263 total posts, approximately 1,618.42 posts (SD = 1, 280.44) per group. Posts most commonly expressed overall positive emotions ($M = 7.58$, SD = 6.52), followed by overall negative emotions ($M = 1.73$, SD = 1.25). Within negative emotions, there were specific expressions of anxiety ($M = .45$, SD = .60), sadness ($M = .40$, SD = .66), and anger ($M = .27$, SD = .35). A paired-samples t-test showed that group members expressed more positive than negative emotions overall ($t(608) = 21.10$, $p < .001$). Among the specific negative emotions, anxiety was expressed more often than anger ($t(608) = 6.50$, $p < .001$), but not sadness ($t(608) = 1.44$, $p = .150$), with sadness expressed more often than anger ($t(608) = 4.45$, $p < .001$). These emotional expression scores were comparable to those observed in other samples including Twitter users (Pennebaker et al. 2015).

On upbeat emotional tone, group members rated about average relative to the LIWC benchmark ($M = 54.12$, SD = 12.79); that is, most members ($n = 385$, 63.2%) had moderate scores on emotional tone (percentiles ranging from 40–59.99). However, a sizeable minority

(n = 166, 27.3%) had more upbeat scores (percentiles ≥ 60), and a smaller minority (n = 58, 9.5%) had more downbeat scores (percentiles < 40). Women expressed more negative emotions ($t(607) = -3.38$, $p = .001$) and anxiety ($t(607) = -3.31$, $p = .001$) and a more upbeat emotional tone ($t(607) = 2.02$, $p = .044$) than did men, but emotional expressions did not differ between members of coed versus women-only support groups (all $p > .05$).

At 1 month, 247 (40.6%) of the group members reported abstinence from smoking, while 362 (59.4%) were nonabstinent. A 1-month abstinence rate of 40.6% is comparable to the efficacy of medication and behavioral counseling in a recent, large clinical trial (Anthenelli et al. 2016). Group members who were abstinent expressed fewer negative emotions overall ($B = -.26$, $p = .005$, $d = -.30$) and specifically anxiety ($B = -.61$, $p < .001$, $d = -.31$), compared to those who were nonabstinent. In contrast, abstinent members had a more upbeat emotional tone ($B = .02$, $p = .003$, $d = .28$). Abstinent and nonabstinent members did not differ in their expressions of positive emotions overall ($B = .01$, $p = .650$, $d = .06$), or the specific negative emotions of anger ($B = -.08$, $p = .739$, $d = .03$) or sadness ($B = -.22$, $p = .555$, $d = .11$). The covariates were not significantly related to abstinence in any of the models, nor was use of nicotine replacement therapy ($\chi^2 = 2.27$, $p = .132$). In post-hoc analyses, the study covariates (participant demographics and support group composition) were tested as possible moderators, to explore whether they might have altered the relationship between emotional expression and abstinence. No notable patterns were identified.

DISCUSSION

Online quit-smoking support groups provide an important outlet for connecting with others trying to quit, obtaining social support and expressing emotions. This study examined whether automated or computerized text analysis may provide a low-cost, low-burden strategy for monitoring group members' emotions and directing tailored mood management to group members who may benefit from it. Using the popular LIWC text analysis software, we scored the positive and negative emotions expressed by members of 36 online quit-smoking support groups. During the first month of these groups, expressions of overall negative emotions, and anxiety specifically, related to smoking nonabstinence at month end. Conversely, a more upbeat emotional tone (i.e., more positive than negative expressions) related to smoking abstinence at month end. These results suggest that automated text analysis can identify emotions expressed in online quit-smoking support groups that are associated with abstinence, offering a possible way to intervene in real time with targeted and meaningful mood management support.

Positive emotions were most commonly expressed, followed by negative emotions. Within negative emotions, anxiety and sadness were more commonly expressed than anger. The more common expressions of positive emotions may be partly due to the nature of online support groups, in which members often provide encouragement to one another (Burri, Baujard, and Etter 2006; Pechmann et al. 2015; Cole-Lewis et al. 2016). Members may have also felt emotions that they did not express (e.g., more anger). This issue is not unique to the online support group context, as people are susceptible to social influence and the desire for positive self-presentation even in dyadic and face-to-face interactions (Goffman 1959;

Hatfield, Cacioppo, and Rapson 1993). Notwithstanding, the groups offered an outlet for sharing negative emotions as well as positive ones, with discussion prompts that encouraged both. The automated text analysis detected both positive and negative emotions that related to smoking abstinence.

As we hypothesized, expressions of negative emotions overall, or anxiety specifically, in group members' posts during 1 month related to nonabstinence at month end, while expressions of sadness and anger were unrelated to abstinence. Using automated text analysis to detect negative emotions and anxiety may be more fruitful than trying to identify sadness or anger, if the goal is to aid in abstinence. In our study, expressions of positive emotions overall were not associated with abstinence. Many group members who experienced positive emotions may have also experienced negative emotions that ultimately hampered their quit attempts. Consistent with this reasoning, members who expressed an upbeat (versus downbeat) emotional tone were more likely to be abstinent.

This study did not find significant differences in emotional expressions when comparing the members of women-only versus coed support groups. However, our results could be largely driven by the female group members, who were more prevalent and who expressed more negative emotions and anxiety, and a more upbeat emotional tone, than males. Thus, assessing men-only groups could be informative. In addition to group members' gender, group size likely affected engagement. Our groups had 20 members to reflect the mean number of active members in naturally occurring online networks (Trusov, Bodapati, and Bucklin 2010). However, group size and other factors that may influence engagement should be studied in formative work to develop online support groups (Arigo et al. 2018).

Implications

Our results have implications for research on emotions and addiction, quit-smoking interventions, and the overall development and implementation of mobile health (mHealth) interventions. Results suggest that automated text analysis of posts in online support groups can yield useful insights with practical significance. Relationships between emotional expressions and abstinence from smoking were in the expected directions and lend support to text analysis, specifically the LIWC text analysis software, as a valid measurement tool that captures a wide range of meaningful emotional expressions.

Negative emotions expressed in online support groups for quitting smoking, particularly when not balanced by positive emotions, may indicate increased smoking relapse risk. Additional resources, including direct outreach, could be directed to support group members who are struggling to manage difficult negative emotions during their quit attempt. Promoting an upbeat emotional tone may also help to facilitate quitting smoking. Targeted messaging could encourage group members to engage in pleasant activities and bolster their supportive social relationships. In our support groups, members received tailored daily messages on their prior-day engagement, which could be augmented to address their prior-day emotional expressions as well. Our discussion prompts targeted to the entire group could also encourage positivity by asking members to share their positive emotions and pleasant experiences. Text analysis could be further used to monitor the "emotional temperature" of the group as a whole and assess the group's needs on an ongoing basis.

Our results also suggest that developers of quit-smoking apps should consider supplementing their digital tools with human support groups that allow people to express their emotions and request advice and support from peers in coping with negative emotions and anxiety. Quit-smoking apps may also seek to directly prime an upbeat emotional tone and distract from negative emotions and anxiety.

Limitations and Future Research Directions

This study has several limitations. An automated text analysis program such as LIWC cannot provide a complete picture of individuals' emotional experiences. Text analysis may be superior to self-report measures in some ways, such as facilitating real-time capture of emotions and avoiding self-report biases. However, text analysis can only capture the emotions individuals are willing to express publicly. In addition, LIWC's dictionary of emotions is not fully comprehensive and lacks specific positive emotions. Future research could develop and test a more customizable text analysis tool to capture a fuller spectrum of emotional expression, including specific positive emotions. Although we used a standard measure of abstinence from smoking (called 7-day point prevalence abstinence), some people may have falsely reported abstinence. Also, for people who quit smoking and then relapsed, it is unclear whether their expressions of negative emotions and anxiety precipitated their lapse. Future research could examine the timing of lapses in relation to expressions of negative emotions and anxiety. The correlational nature of our secondary data analysis precludes claims about the causal effects of emotional expressions on abstinence. The vast majority of the social media posts that we studied temporally preceded our measure of abstinence, and our analyses adjusted for potential confounding factors; however, the causal effects of emotional expressions on abstinence cannot be confirmed. Future research should also test the efficacy of specific mood management interventions on smoking abstinence.

Moving Forward on Addiction and Maladaptive Consumption: Contextualizing Emotions

Emotions experienced in daily life can be triggered by a complex interplay of internal and external cues. In addition to detecting emotions, text analysis could be used in online support groups to detect keywords reflecting the situational context in which emotions occurred. Specifically, text analysis could identify themes in situations that drive negative emotions and subsequent relapse. For example, feelings of shame resulting from not meeting one's own standards can drive maladaptive consumption (Chang, Jain, and Reimann 2021). Other complex contextual factors may also influence decisions to smoke or not smoke; for instance, saving a cigarette for later may increase its perceived value (Rifkin and Berger 2021), and feeling as though "lady luck" is on one's side may reduce the perceived risks of smoking (Kulow, Kramer, and Bentley 2021). Moreover, individuals struggling with addictive behaviors (e.g., smoking) tend to pay more attention to novelty in the environment because of a need for psychological fulfillment. Experiencing self-satisfaction or pride can ameliorate the need for psychological fulfillment (van Esch and Cui 2021). Sophisticated text analysis programs may detect complex emotions and situational contexts, such as shame, luck, and pride.

Feedback from text analysis could also help support group participants monitor their own emotions and the effects of their emotions on their smoking behavior. Contextual cues can help people accurately assess their own addictive behaviors (Raghubir, Menon, and Ling 2021). Reflecting on emotions that precipitated behavior, as well as situational factors (e.g., intoxication at the time of the behavior) can influence people's views of culpability for a behavior (Galoni, Goldsmith, and Hershfield 2021) and may encourage self-reflection. Research has shown that participants enjoy tracking their smartphone usage (Zimmermann 2021), and tracking emotions expressed on social media may be appealing as well.

In addition to smoking, future research could examine whether emotions identified by text analysis also predict engagement in other forms of maladaptive consumption (e.g., shopping, gambling), as addictive behaviors frequently co-occur and may share underlying mechanisms (Clithero, Karmarkar, and Hsu 2021; Turel and Bechara 2021). Examining additional behaviors would further contextualize the situations in which emotions and addictive behaviors occur. Identifying causal explanations for addictive behaviors can be challenging (Reimann and Jain 2021). Nonetheless, text analysis can provide insight into the context in which emotions may precipitate smoking relapse and other addictive behaviors.

CONCLUSION

In conclusion, online support groups for quitting smoking offer an outlet for rich emotional expressions during the often tumultuous behavior change process. Automated text analysis can capture the emotions expressed in group members' posts and help direct tailored messaging and support toward group members who need it on the basis of their expressions of strong negative emotions and anxiety. Supportive messaging can also encourage members who experience more positive than negative emotions to maintain their positive outlook. In sum, automated text analysis can help practitioners provide targeted support for mood management in online quit-smoking support groups.

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