Commentary on Cohn and Colleagues: Discussions of Alcohol Use in an Online Social Network for Smoking Cessation: Analysis of Topics, Sentiment, and Social Network Centrality (*ACER*, 2019)

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IT IS WELL understood that cigarette smokers consume alcohol more frequently and in higher amounts than non-smokers (Falk et al., 2006; Kahler et al., 2008, 2010). In addition, among heavy drinkers in smoking cessation treatment, alcohol consumption is associated with increased risks of smoking relapse (Kahler et al., 2010). A recent study by Cohn and colleagues (2019) examined the impact of alcohol consumption during a quit attempt among individuals seeking smoking cessation support online. The investigators sought to determine the characteristics of users that posted prevalent alcohol-related topics, as well as general clarity about the type of conversations all users of the platform had about alcohol. As in previous findings, alcohol use was associated with a recurrence of tobacco use during a quit attempt. Data from social networking sites and message boards can also be used to gain psychological insights. Indeed, Cohn and colleagues (2019) observed a relationship between alcohol use and celebratory discussions of quit milestones; gained a deeper understanding of the positive sentiment toward alcohol-related content in these networks; and observed how alcohol conversations varied by users' social connectivity in the network.

This is the first study to examine how co-occurring alcohol use impacts the support received (and provided) on online smoking cessation platforms. The findings by Cohn and colleagues (2019) provide the first look into user-level sentiment and discourse patterns involving alcohol in a tobacco cessation digital intervention. As digital interventions have historically mirrored the static content from physical interventions (i.e., curriculum-based static content), the results suggest that digital interventions should instead use dynamic content that is variable based upon user characteristics and real-time sentiment or linguistic analysis. For example, new users who are early on in their tobacco quit attempt were more likely to express negative sentiment toward alcohol content, as well as express cravings and temptations parallel with both alcohol and tobacco. Compared to more experienced users, who were abstinent from tobacco for a longer period of time and more socially connected on the platform, this shows a categorical difference in both needed intervention content—such as material focused on cravings and temptations for new users—and helping users grow their social connections, while minimizing potentially emotionally triggering content from more experienced users who were often virtually toasting.

The use of technology to better understand and intervene in substance use behaviors, including both licit substances (e.g., tobacco and alcohol) and illicit substances (e.g., non-prescription opioids and cannabis), has become increasingly common (Dedert et al., 2015; Nesvåg and McKay, 2018). In part, this movement to integrate technology into addiction treatment is a result of high treatment demand, limited treatment availability, and a growing familiarity of the treatment population with obtaining health information and support online. Consequently, researchers are adapting evidence-based programs to be delivered via digital platforms (Nesvåg and McKay, 2018). Here, we comment on the use of online language to gain insights into substance use and alcohol-related behaviors and how technology can be used to better understand and intervene in relapse.

ONLINE SOCIAL AND SUPPORT NETWORKS

Obtaining health information and support online is well integrated into our lives. Over 70% of adult Internet users report searching online for health information, specifically information about diseases and treatments (Pew Research Center, 2014). In addition, these users report having read accounts of health experiences and have posted about their own experiences (Pew Research Center, 2014). Online social support networking sites facilitate the sharing of information

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and promote social engagement. For substance using individuals and those in recovery, the use of public social networking sites (e.g., Reddit, Facebook, and Twitter) and proprietary platforms (e.g., Sober Grid, WEConnect, and MyFYR) is believed to replicate the in-person social networks that derive from community connection—perhaps most well-known from the study of networks of mutual aid programs and communities such as 12-step mutual aid groups (Best et al., 2016; Kelly and Moos, 2003; Kelly et al., 2014). Digital spaces such as these also have the ability to augment and complement the social supportive services with more formalized supports such as peer recovery coaching (Bassuk et al., 2016), recurrence of use risk factor predictions (McKay et al., 2016), and even a more diverse set of community connections for minority communities (e.g., veterans, LGBTQ+, youth, and emerging adults) (Bergman et al., 2017). Though the use of social networking sites for substance use disorder recovery is still new, a recent study of outpatient treatment clients found that a majority of clients had both the means (e.g., owned a smartphone and accessed Internet and social networks daily) and the interest in receiving recovery-related information and services via digital means—social networking sites, smartphone apps, SMS text messaging, or via websites (Ashford et al., 2018). Thus, continuously identifying the efficacious mechanisms for the digital infrastructure, ways in which individuals use existing platforms, and the different types of health-related behaviors, such as problematic alcohol or drug use, is needed.

SOCIAL MEDIA LANGUAGE AND ALCOHOL CONSUMPTION

The widespread usage of social media networks and message boards provides patients with access to a wealth of information and peer support. Data from these digital platforms allow researchers to examine both unique relationships that would be near impossible to examine with traditional data sources, and provide real-time examination of relationships, such as binge drinking rates (Curtis et al., 2018a), used in public health and prevention domains. While these platforms are emerging as a viable place to obtain individual and aggregate health information, social networking sites are also a place of alcohol and drug exposure. For example, observational analysis of social networking sites has identified problematic prescription opioid use (Carrell et al., 2015), nonmedical use of psychostimulants (Hanson et al., 2013), and excessive alcohol consumption (Curtis et al., 2018a). Similarly, a recent meta-analysis conducted by Curtis and colleagues (2018b) reported a significant relationship between posting alcohol-related content on social networking sites and alcohol consumption behavior and alcohol-related consequences. While the use and study of social networking sites and digital recovery platforms—such as smartphone applications—remain in its infancy in many ways, preliminary studies suggest that it is useful for observation and identification of substance use behaviors and risk, as well as a potential location for dissemination of health-focused communication focused on reducing risk and increasing healthy behaviors (Miller and Sønderlund, 2010).

The words people use in their daily lives reveal important insights into their lives (Rude et al., 2004; Tausczik and Pennebaker, 2010). Researchers have long shown that language is an indicator of health status. For example, there are correlations between "angry" language and heart disease and between "positive emotional language" and longevity (Danner et al., 2001; Graham et al., 1989). Oxman and colleagues (1988) conducted a study with patients from 4 diagnostic groups (somatization, paranoid, major depression, and cancer) to test whether patients could be accurately classified back into their appropriate diagnostic groups by 2 psychiatrists using purely lexically based system of content analysis. The results suggest that data from the lexicon-based analysis did accurately classify patients into their respective diagnostic groups (Oxman et al., 1988). Multiple studies have also examined social media language patterns and associated sentiment toward cannabis (Daniulaityte et al., 2016), cigarettes (Myslín et al., 2013), prescription medications (Shutler et al., 2015), and alcohol (Cavazos-Rehg et al., 2015). Sentiment analysis applied in this way has been mostly limited to the classification of a positive or negative view of substances, and several limitations to the automated sentiment analysis method have been noted (Daniulaityte et al., 2016). This limitation—lexicon-based sentiment analysis may incorrectly classify substance-related tweets as negative when they are in fact positive as traditionally negative language can be positive when used in the context of substance-related content—is mitigated through the use of manual coding procedures (i.e., real-world research staff coding) but is time-consuming and resource intensive. Cohn and colleagues (2019) utilized a hybrid approach (first described in an earlier work; Cohn et al., 2017) that began with human coders creating a framework and then teaching a machine classifier to automatically code the remaining posts.

PREDICTING RELAPSE

The literature on relapse identifies numerous methodological inconsistencies, with heterogeneity in the definition of relapse, assessment methodologies, and models of relapse-related factors (Donovan, 1996; Hendershot et al., 2011; McKay, 1999). McKay (1999) reviewed divergent methodologies for collecting data on relapse including the following: (i) retrospective reviews in which participants are asked to recall instances of relapse and the factors preceding them; (ii) prospective reports, in which information about potential antecedents is collected at baseline or periodically and then examined for association with a detected relapse; and (iii) near real-time reports, in which participants are asked or electronically prompted to report on factors near the actual time of relapse. Near real-time reports are optimal because relapse vulnerability factors such as mood, craving, stress, motivation, and social support can change over a period of a few hours (McKay et al., 2006). In the context of these challenges, Cohn and colleagues (2019) demonstrate the feasibility of using online language as a tool to detect and predict relapse and correlating behaviors in near real time.

SUMMARY AND FUTURE DIRECTIONS

The work by Cohn and colleagues (2019) advances science not only by employing machine learning in the fields of addiction, but also by the use of correlated topic modeling to identify language associated with alcohol-related posts. This has the potential to yield important clinical advances. First, this approach will provide health providers with a framework to identify factors that place patients at risk. Second, this approach may identify new variables of importance in predicting relapse. Third, these predictive models can be used to develop a relapse vulnerability feedback tool that can be integrated into an online intervention. This could have implications for novel approaches to clinical research and practice as applications could be developed to automatically intervene with the patient. For example, discussions of celebrations in a patient's online communications would lead to a message being sent to the patient alerting them of an increased risk of relapse and recommending coping strategies or scheduling additional therapeutic sessions. Because relapse is an area of concern for many chronic medical conditions outside of addictions (e.g., asthma and diabetes), this technology could have widespread benefits in medicine. Finally, detecting risk of relapse through relatively inexpensive technology that provides a window on a patient's daily behavior could allow early interventions, thereby potentially reducing the need for more costly treatment once the patient's condition worsens. To the extent that interventions and health messages could be delivered automatically in response to the detection of increased risk, healthcare costs could be able significantly curtailed.

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