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Discussions of alcohol use in an online social network for smoking cessation: analysis of topics, sentiment, and social network centrality

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Abstract

Background: Few Internet smoking cessation programs specifically address the impact of alcohol use during a quit attempt, despite its common role in relapse. This study used topic modeling to describe the most prevalent topics about alcohol in an online smoking cessation community, the prevalence of negative sentiment expressed about alcohol use in the context of a quit attempt (i.e., alcohol should be limited or avoided during a quit attempt) within topics, and the degree to which topics differed by user social connectivity within the network.

Methods: Data were analyzed from posts from the online community of a larger Internet cessation program, spanning January 1, 2012 to May 31, 2015 and included records of 814,258 online posts. Posts containing alcohol-related content (n = 7,199) were coded via supervised machine-learning text classification to determine whether the post expressed negative sentiment about drinking in the context of a quit attempt. Correlated Topic Modeling (CTM) was used to identify a set of 10 topics of at least 1% prevalence based on the frequency of word occurrences among alcohol-related posts; the distribution of negative sentiment and user social network connectivity were examined across the most salient topics.

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CONLFICTS OF INTEREST
There are no conflicts of interest to declare.

Results: Three salient topics (with prevalence ≥ 10%) emerged from the CTM, with distinct themes of (1) cravings and temptations; (2) parallel between nicotine addiction and alcoholism; and (3) celebratory discussions of quit milestones including "virtual" alcohol use and toasts. Most topics skewed toward non-negative sentiment about alcohol. The prevalence of each topic differed by users' social connectivity in the network.

Conclusions: Future work should examine if outcomes in Internet interventions are improved by tailoring social network content to match user characteristics, topics, and network behavior.

Keywords

Alcohol; smoking; quitting; relapse; topic modeling; online cessation; text mining; social networks

INTRODUCTION

Cigarette smoking is the leading cause of preventable death and disability in the United States (Rostron et al., 2014, Ma et al., 2018). Despite the strong relationship between smoking and cancer-related morbidity and mortality and the noted health benefits of quitting (Siegel and Jemal, 2015, Adhikari et al., 2009, Bjartveit and Tverdal, 2009), very few smokers quit every year (Jamal et al., 2015), and the majority of those who do quit relapse within the first year (Fiore et al., 2000, Piasecki, 2006, Hughes et al., 2004). A subset of smokers who are unable to quit successfully possess vulnerability characteristics, like mental health or substance use problems, that impede quit success (Lê Cook et al., 2014, Centers for Disease Control and Prevention, 2013, Kessler et al., 2005, Hasin et al., 2007, Talati et al., 2016).

A robust literature shows that alcohol involvement and heavy drinking, which are highly co-morbid with cigarette smoking (Kahler et al., 2009, Kahler et al., 2008), are associated with increased risk for smoking persistence, smoking relapse, and lower odds of success at quitting (Le Strat et al., 2010, Falk et al., 2006, Cargill et al., 2001). In fact, the co-use of tobacco and alcohol is significantly more prevalent than the use of either substance alone (Falk et al., 2006). Nearly half of all problem drinkers are nicotine dependent (Falk et al., 2006, Le Strat et al., 2010), and most relapses following a quit attempt are attributed to a drinking episode (Kahler et al., 2009, Kahler et al., 2010, Sells et al., 2017). A recent population-based analysis of US adults assessed from 2002 to 2015 found that the smoking quit rate was nearly two times lower among smokers with an alcohol use disorder than without (Weinberger et al., 2017). Understanding the role of alcohol use among smokers engaged in a quit attempt may facilitate progress towards reducing the population prevalence of cigarette smoking, by supporting more effective treatment.

More than 12 million smokers search online for information about quitting smoking each year (Graham and Amato, 2018). Evidence-based cessation interventions that deliver individually tailored information and leverage the interactivity of the Internet yield quit rates that are comparable to face-to-face and quitline interventions (Taylor et al., 2017, Graham et al., 2016). Tailoring can vary in the amount and source (Taylor et al., 2017) and the constructs used for tailoring. The most common constructs used for tailoring are self-reported level of readiness to quit, self-efficacy and barriers to quitting, but abstinence status, goals and motivations for quitting, and testimonials are used as well (Milward et al., 2018). One unique advantage of Internet cessation programs is their ability to provide users with ready access to online social networks of both current and former smokers to exchange information and support. Health information from peers can be a powerful driver of behavior, yet little is known about the influence of online social network discussions on smoking and quitting. The availability of user-generated content from an online social network for smoking cessation provides a "living laboratory" of sorts to examine how smokers engaged in the process of quitting talk about alcohol use. This kind of "self-report" data may also represent a novel approach to intervention tailoring.

A number of studies have examined the ways in which online social networks can support changes in problem drinking behavior (Urbanoski et al., 2017, Cunningham et al., 2008). In a study of smokers participating in an online cessation intervention, Cunningham et al. (Cunningham et al., 2006) reported that one-third of current daily smokers were problem drinkers (24% of occasional smokers and 22% of former smokers were current problem drinkers). The majority of daily smokers who were current drinkers reported they frequently or always experienced a strong urge, desire or thoughts about smoking when they drank alcohol. To date, we are aware of only one study that has focused on alcohol-related discussions in an online social network for smoking cessation (Cohn et al., 2017). Using a blend of sentiment analysis and social network analyses, Cohn et al. found that users who posted in favor of limiting or avoiding alcohol while quitting smoking were more socially connected to other network members than were users who did not express sentiment that alcohol should be avoided. The next steps in this line of work are understanding of the different types of conversations users have about alcohol and determining the extent to which alcohol-related conversations signal that alcohol use in the context of a quit attempt is an influential factor in the relapse process. Diffusion of, and exposure to, information within a social network can be a powerful tool for behavior change (Christakis and Fowler, 2013, Wang et al., 2014, Aral and Nicolaides, 2017). Yet, little is known about the content of alcohol-related discussions in an online social network for smoking cessation.

The goals of this paper were to provide greater clarity on the types of conversations users have about alcohol, and to identify user characteristics associated with prevalent alcohol-related topics. We began with topic modeling to identify and describe the most salient topics about alcohol in the social network. Next, we examined the distribution of negative sentiment towards use of alcohol during a quit attempt – that is, sentiment that alcohol should be reduced or avoided during a cessation attempt – within the most prevalent alcohol-related topics. Finally, we examined whether types of conversation topics about alcohol within the social network differed by individuals' social network centrality. Classifying the ways in which centrally and peripherally connected users discuss alcohol in an online social network for cessation will provide insight into the types of information users need about alcohol's deleterious role in the quit process.

MATERIALS AND METHOD

Data Source

Data came from BecomeAnEX.org, a web-based smoking cessation program developed and managed by Truth Initiative in collaboration with Mayo Clinic Nicotine Dependence Center. The site was launched in 2008 and has delivered evidence-based cessation treatment (Fiore et al., 2008) to more than 800,000 registered users. The site includes a large social network of current and former smokers who connect via multiple communication channels: private messages, public posts on member profile pages ("message boards"), group discussions, and blog posts. Blogs post and comments, message boards, and group discussions are public communications that can be viewed by all BecomeAnEX users.

The dataset spanned January 1, 2012 to May 31, 2015 and included records of 814,258 online activities contributed by 9,377 users, including both posting and reading events. To protect privacy, the content of private messages was not included in the dataset. The study protocol for these analyses was reviewed and approved by Chesapeake Institutional Review Board (protocol #00010302).

Analytic Plan

Topic modeling: We took a two-stage approach to analyze alcohol-related conversation topics using Correlated Topic Modeling (CTM), an unsupervised machine learning technique that identifies a set of latent topics based on the frequency of word occurrences that occur in a large set of text data (Blei and Lafferty, 2007). Specifically, CTM generates separate probability distributions over a fixed set of keywords (vocabulary) for each one of a user-specified number of topics. The relative frequency of each keyword within a particular topic helps characterize the topic itself and allows us to assign it a descriptive identifier. The probability that a post belongs to a particular topic is then calculated as the proportion γ of keywords within that post indicative of the topic. An advantage of CTM over alternative approaches such as Latent Direchlet Allocation (LDA) is that topics in CTM may be correlated with each other, more closely approximating nature where discussion topics frequently overlap in content.

Following methodology reported previously (Cohn et al., 2017), the first step of topic modeling was to identify all posts that included any alcohol content. Briefly, we developed a machine-learning-based text classifier that determined if a post was (or was not) about alcohol use. Four independent machine classifiers were trained on a subset of posts that had been manually coded by domain experts, who were recruited from the online community. Posts via blogs (and comments), message boards, and threaded group discussions were used. I Individual comments were treated as independent posts. A sub-set of 1,850 posts that contained at least one word from a pre-specified list of alcohol-related keywords were first manually coded by domain experts to determine if the post contained a reference to alcohol use. These posts were then used to train the machine-classifier using machine learning algorithms. The best-performing classifier was identified using Area under the ROC (AUC) from 10-fold cross validation, and was then applied to all other posts that also contained at least one alcohol keyword.

The CTM analysis included posts identified as alcohol-related by the classifier (6,527 posts), as well as the smaller subset of alcohol-related posts contained in the training set (672 posts), for a total of 7,199 posts. For example, posts that included mentions of alcohol keywords (“drink”), but which were not about alcohol use (“drink coffee”), were not included in analyses. There was further refinement of posts included in the CTM, including removal of duplicate posts, removal of stop-words (e.g., “an”, “the”, and “of”), and stemming (e.g., converting “smoking” to “smoke”). After this refinement phase, the total number of alcohol-related posts decreased to 6,095 contributed by 1,084 users (median posts per subject = 1, interquartile range = 1–4, max= 244). A total of 26,624 distinct keywords were present in these posts, with the typical post averaging 48 keywords in length. CTM was then applied to these posts, and the number of pre-specified topics was increased iteratively in unit steps until any additional topics thus identified had less than 1% prevalence as determined by mean allocation. CTM was implemented with the ‘topicmodels’ package version 0.2–7 with R version 3.4.3.

To interpret the most salient topics, we then focused on all topics with prevalence ≥ 10%. After CTM-derived topics were identified, themes were extracted by the first two authors, who reviewed keywords and the 10 most representative posts for each topic. Representativeness was determined by the proportion γ of keywords in each post associated with the respective topic.

Prevalence of topics was estimated using two distinct methods: mean allocation and modal allocation. Mean allocation more accurately represents the relative frequency of each topic at the corpus level. In CTM, each post is not associated with a single topic, but rather is assigned a probability distribution over all topics. For example, 40% of alcohol-related keywords in an individual post may be associated with Topic A; 30% with Topic B; and 30% with Topic C. Mean allocation estimates the overall prevalence of topic A by averaging the relative frequency of Topic A keywords across all posts. In contrast, modal allocation uses a “majority-rules” approach: each post is first assigned to the topic with the greatest probability, and then topic frequencies are averaged across posts, rather than across keywords. Modal allocation was used in the analyses exploring associations of topics with sentiment and network position, because this approach allowed those analyses to be conducted with a parsimonious approach that associated each post with one unique topic, rather than a less parsimonious approach based on fractional allocation of each post across multiple topics.

Association of negative sentiment about alcohol use and topics: Next, we investigated whether the likelihood of negative sentiment about use of alcohol during a quit attempt in a post varied across topics. In a previously published study (Cohn et al., 2017), posts containing alcohol-related content were coded via supervised machine-learning text classification to determine whether the post expressed negative sentiment about drinking in the context of a quit attempt (i.e., alcohol should be limited or avoided during a quit attempt). Annotations of sentiment focused only on negative sentiment to align with tobacco dependence treatment guidelines that alcohol should be avoided or limited during a cessation attempt (Fiore et al., 2008). The machine-learning-based sentiment classification was done with the ‘scikit-learn’ package (version 0.18.1) in Python 2.7.11. Details about sentiment classification of alcohol-related posts can be found in (Cohn et al., 2017). Briefly, human coders annotated a training set of posts for the presence of negative sentiment towards drinking alcohol during a quit attempt, and a machine classifier was then trained and applied to all remaining posts in the network. Features for the sentiment classifier included meta features (e.g., length of posts), as well as unigrams weighted by TF-IDF and their distances to alcohol keywords. We did not use any lexicon dictionary. To simplify analyses looking at between-topic differences in the proportion of posts expressing negative sentiment towards alcohol, each post was classified as belonging exclusively to its most prevalent topic (modal allocation). We used generalized estimating equations for nominal multinomial data with a generalized logit link, as implemented in SAS/STAT 14.1 (2017), to correct for correlation across posts by the same author when testing for association of topics and sentiment towards alcohol use during a quit attempt. Author ID was used as the cluster identifier.

Association between social network connectivity and topics: Finally, we examined whether the way users talked about alcohol varied by their level of connectedness in the social network. User social network position was operationalized by computation of “in-degree” and “out-degree” centralities, with higher values reflecting greater social network connectivity. The social network was constructed by examining users’ reading and posting behaviors, where each user is represented as a node. For example, there is a tie pointing from Mary to John if John read a post published by Mary. In other words, ties are based on the flow of information either “toward” or “away from” a user (Krippendorff, 2012). A user’s in-degree reflects the total number of members the user had been exposed to by reading their posts; out-degree reflects the total number of members who had read the content posted by the user (Zhao et al., 2016). The whole network, which was constructed and analyzed with the ‘NetworkX’ package (version 1.11) of Python 2.7.11, consisted of N=71,251 users in the community, but our subsequent study focused only on a sub-sample of 1,084 users who posted about alcohol use.

The sample was stratified into three groups as a function of those in the top third, middle third, and bottom third (separately) for “in-degree” and “out-degree;” we then tested whether the relative frequencies of topics varied by user group. Three groups were chosen because approximately one third of users had maximum degree by both metrics, precluding separation into a larger number of meaningful groups. For the purpose of these analyses, each post was again classified as belonging exclusively to its most prevalent topic (modal allocation). We used generalized estimating equations for correlated nominal multinomial data with a generalized logit link, as implemented in SAS/STAT 14.1 (2017). A significant overall multinomial test, indicating non-independence of topics and user groups, was followed-up with separate binomial models for differences in the prevalence of each topic by user group.

RESULTS

Topic Modeling Results and Topic Themes

Table 1 shows the most representative words for each of the 10 topics extracted from the CTM of 6,095 posts (duplicates removed), with 26,624 unique lexemes. Word representativeness was based on how frequently the word appeared in each respective topic relative to all other topics. Theme extraction yielded three topics (2,4,9) that were most salient (prevalence of ≥ 10.0% out of all topics), as others were rare/infrequent. Combined, these three topics represented 82.0% of all posts (by modal allocation). Table 2 shows the most representative posts from each of the three salient topics; topic themes from each of these three topics are described below, presented in ascending topic order (not by topic prevalence).

Topic 2: Cravings and Temptations around Alcohol.—The second most prevalent topic (21% of posts based on mean allocation; 16.2% of posts based on modal allocation) focused on discussion of situations or settings in which recent quitters felt tempted to smoke in the presence of alcohol. Settings included bars (post 1), neighbors' homes (post 2), and the users' own homes (post 3). Social interactions included friends (post 1), neighbors (posts 2, 3), and partners (post 3).

Topic 4: Similarities of Nicotine Addiction to Alcoholism.—The most prevalent topic (43% of posts based on mean allocation; 50.3% of posts based on modal allocation) included discussions centered around alcoholism. Alcoholism was used as a metaphor to communicate the power of nicotine addiction (posts 4, 5 from Table 2). Alcoholism was also used to illustrate the importance of recognizing the ways in which substances can be used as a maladaptive behavior for coping with stress or negative affect (post 6). Posts in topic 4 tended to be written by former smokers, offering advice to current smokers and recent quitters.

Topic 9: Alcohol for Celebrations.—Like many communities, BecomeAnEX has traditions that reinforce shared values and connectedness among members. Posts in the third most prevalent topic (14% of posts based on mean allocation; 15.4% based on modal allocation) were related to one such tradition with the BecomeAnEx community, the Freedom Train, in which members celebrate their freedom from tobacco addiction (posts 7, 8, 9). Members participate by posting supportive messages to each other (posts 8, 9) and by celebrating quit-related milestones by virtually "toasting" each other with mentions and images of drinks (often times alcoholic drinks) and snacks (posts 7, 8, 9).

Association of Negative Sentiment about Alcohol Use and Topics

Out of 4,995 posts across the three most prevalent alcohol-related topics, only 1,725 (35%) expressed negative sentiment about alcohol use during a quit attempt; however, the distribution of sentiment differed by topic ($p < 0.001$), as shown in Table 3. For both Topic 2 (*Cravings and Temptations around Alcohol*) and Topic 4 (*Similarities of Nicotine Addiction to Alcoholism*), the proportions of posts expressing negative sentiments were close to that of the overall sample (36.2% and 36%, respectively). As expected, Topic 9 (*Alcohol for Celebrations*) posts were much less likely to express negative sentiment about alcohol use during a quit attempt (27.9%).

Association Between Social Network Connectivity and Topics

Table 4 shows the distribution of posts in each topic by user in-degree and out-degree (low, medium, and high). The χ^2 tests for Topics 2 and 4 were significant for both in-degree and out-degree (all p's < .001), indicating that the proportion of posts in each topic differed by authors' social network connectedness. Posts on Topic 2 (Cravings and Temptations around Alcohol) were roughly 2.5 times more frequent among users with low-to-medium connectedness than users with high connectedness, measured by both in-degree and by out-degree. In contrast, posts on Topic 9 (Alcohol for Celebrations) were most common among highly connected users. Among users with high in-degree, posts in Topic 9 were 4 times more likely compared to users with low in-degree, and twice as likely compared to users with medium in-degree. A similar pattern was observed for posts on Topic 9 based on out-degree. Interestingly, posts on Topic 4 (Similarities of Nicotine Addiction to Alcoholism) showed no differences across groups based on out-degree (p=.913), and smaller differences by in-degree user group, being about 5% more prevalent among low in-degree users than medium-to-high users (p=.036).

DISCUSSION

This study is the first to our knowledge to examine the content of alcohol-related discussions within an online social network for smoking cessation. Correlated Topic Modeling revealed three salient topics about alcohol use: 1) discussions of cravings and temptations related to alcohol use, 2) similarities of quitting tobacco to quitting drinking, and 3) celebratory posts with virtual alcohol-related "toasts" for achieving tobacco cessation milestones. Negative sentiment about alcohol use across these three topics was detected in roughly one third of posts, with non-negative sentiment being normative. The topics that users posted about varied by users' connectedness in the network. Posts about craving and temptations related to alcohol use were most common among less socially connected users within the community, likely indicating newer users who were actively in the process of a quit attempt. In contrast, posts involving celebrations of cessation milestones were more common among more socially connected users, many of whom have likely been abstinent for several years. Posts about the similarities of quitting tobacco and quitting drinking showed little variability across centrality groups.

Negative sentiment about drinking during a quit attempt was only detected among one third of the posts. Negative sentiment was most common in Topics 2 and 4, which focused on how to manage alcohol during cravings and temptations during a quit, and made similarities between nicotine addiction and alcoholism, respectively. Analyses of degree of social connectivity among users who posted in each topic showed that posts on Topic 2 were more typical of users who have low or moderate centralities within the social network, and less typical among well connected users. Topic 2 focused primarily on dealing with immediate cravings and difficulties related to alcohol use during a quit attempt, which are likely salient issues for newer users who are learning to cope with the early phases of a quit attempt. Posts on Topic 4, in contrast, were equally spread across peripherally and centrally connected users, suggesting that knowledge of the parallel between nicotine addiction and alcohol use problems is widespread and transcends social network position. There is also an interesting paradox to note that alcohol (even if virtual) was used to celebrate cessation milestones within Topic 9 - a topic driven primarily by strongly connected users - while at the same time recognizing, in other topics, users discussed the need to limit or abstain completely from alcohol use to have a successful quit attempt.

This work sets the stage for the development of Internet or other types of digital cessation interventions that could be customized or tailored in real-time based on coding user-generated social network connectivity and content, as well as detecting topic-specific sentiment. Currently, most Internet cessation interventions include static content across a range of topics that users are expected to find and navigate on their own. Such content could be tailored based on users' interest in a particular topic, measured directly from their participation in discussions. For example, identifying users who are seeking information about the pros/cons of avoiding alcohol during a quit attempt could enable the delivery of targeted and individualized content that dispels myths and misconceptions about drinking and encourages abstinence from alcohol. This same real-time tailoring could also feature curated community content that aligns with evidence-based treatment guidelines. Ultimately, the goal of customizing educational and community content is to assist users in considering different perspectives as they formulate their own quit plan. If alcohol use during a quit attempt is stigmatized within an online social network for smoking cessation – particularly by users who are highly influential – less connected members may be hesitant to engage in discussions about alcohol use, missing important opportunities for information or support.

There are several limitations of this study. We did not examine changes over time in the links between social network connectivity and topic frequency. A user's social network connectedness may change over time as s/he becomes more embedded within the community or uses the website more or less often. It is possible that a user's sentiment about alcohol changes over time as they are exposed to more (or less) negative sentiment about drinking within different topics focused on alcohol use. An important next step in this line of work is to determine whether social network dynamics impact sentiment about alcohol use over time, and vice versa. Second, we did not examine whether users exposed to different sentiment about alcohol – particularly negative sentiment – have greater odds of smoking cessation success. Indeed, only a few studies of online cessation programs have examined the degree to which online behaviors impact offline behaviors and smoking cessation outcomes (Amato et al., 2018, Graham et al., 2017) and this would be an important question to explore in subsequent research with respect to alcohol use.

This study adds to the literature in several important ways. While the role of alcohol use in smoking relapse has been widely investigated in offline studies, no prior studies have examined the types of topics involving alcohol use in the online social network for smoking cessation. Identifying the types of discussions about alcohol – and the sentiment toward drinking – that users have in an online network for cessation could shed light on ways to better engage smokers who may be vulnerable to risky drinking behaviors, which put them at-risk for relapse. We used an innovative text mining approach to analyze a large amount of text data, which is novel in the study of online social networks for cessation. The text classification of relevance to alcohol use is more time and cost-efficient than conventional qualitative coding. Text mining through topic models allows latent topics to emerge from a large amount of text data and assigns topics to each document automatically, instead of manually picking topics a priori and associating each post to topics.

Overall, our findings show that when users post about alcohol use in the community of an online smoking cessation program, it is most likely related to drinking-related cravings and temptations among less socially connected users, the links between nicotine and alcohol addiction, or about celebrations for reaching important smoking abstinence milestones among more socially connected users. These findings provide an important foundation for future efforts to deliver a more tailored intervention where social network content may be curated and matched to user characteristics and network behavior.

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REFERENCES

Adhikari B, Kahende J, Malarcher A, Pechacek T & Tong V 2009 Smoking-attributable mortality, years of potential life lost, and productivity losses. Oncology Times, 31, 40–42.

Amato MS, Papandonatos GD, Cha S, Wang X, Zhao K, Cohn AM, Pearson JL & Graham AL 2018 Inferring Smoking Status from User Generated Content in an Online Cessation Community. Nicotine & Tobacco Research

Aral S & Nicolaides C 2017 Exercise contagion in a global social network. Nature communications, 8, 14753.

Bjartveit K & Tverdal A 2009 Health consequences of sustained smoking cessation. Tobacco control, tc. 2008026898.

Blei DM & Lafferty JD 2007 A correlated topic model of science. The Annals of Applied Statistics, 17–35.

Cargill BR, Emmons KM, Kahler CW & Brown RA 2001 Relationship among alcohol use, depression, smoking behavior, and motivation to quit smoking with hospitalized smokers. Psychology of addictive behaviors, 15, 272. [PubMed: 11563809]

Centers for Disease Control and Prevention 2013 Vital signs: current cigarette smoking among adults aged≥ 18 years with mental illness-United States, 2009–2011. MMWR. Morbidity and mortality weekly report, 62, 81. [PubMed: 23388551]

Christakis NA & Fowler JH 2013 Social contagion theory: examining dynamic social networks and human behavior. Statistics in medicine, 32, 556–577. [PubMed: 22711416]

Cohn AM, Zhao K, Cha S, Wang X, Amato MS, Pearson JL, Papandonatos GD & Graham AL 2017 A Descriptive Study of the Prevalence and Typology of Alcohol-Related Posts in an Online Social Network for Smoking Cessation. Journal of Studies on Alcohol and Drugs, 78, 665–673. [PubMed: 28930053]

Cunningham JA, Selby P & Van Mierlo T 2006 Integrated online services for smokers and drinkers? Use of the check your drinking assessment screener by participants of the Stop Smoking Center. Nicotine & tobacco research, 8, S21–S25. [PubMed: 17491167]

Cunningham JA, Van Mierlo T & Fournier R 2008 An online support group for problem drinkers: AlcoholHelpCenter. net. Patient education and counseling, 70, 193–198. [PubMed: 18022340]

Falk DE, Yi H & Hiller-Sturmhofel S 2006 An epidemiologic analysis of co-occurring alcohol and tobacco use and disorders. Alcohol Res Health, 29, 162–171. [PubMed: 17373404]

Fiore M, Bailey W, Cohen S, Dorfman S, Goldstein M, Gritz E, Heyman R, Jaen C, Kottke T & Lando H 2000 Treating tobacco use and dependence. Clinical practice guideline. Rockville, MD: US Department of Health and Human Services.

Fiore M, Jaen CR, Baker T, Bailey W, Benowitz N, Curry SE, Emsp14 Al, Dorfman S, Froelicher E, Goldstein M & Healton C 2008 Treating tobacco use and dependence: 2008 update. Rockville, MD: US Department of Health and Human Services.

Graham AL & Amato MS 2018 Twelve Million Smokers Look Online for Smoking Cessation Help Annually: Health Information National Trends Survey Data, 2005–2017. Nicotine & Tobacco Research.

Graham AL, Carpenter KM, Cha S, Cole S, Jacobs MA, Raskob M & Cole-Lewis H 2016 Systematic review and meta-analysis of internet interventions for smoking cessation among adults. Substance abuse and rehabilitation, 7, 55. [PubMed: 27274333]

Graham AL, Zhao K, Papandonatos GD, Erar B, Wang X, Amato MS, Cha S, Cohn AM & Pearson JL 2017 A prospective examination of online social network dynamics and smoking cessation. PloS one, 12, e0183655. [PubMed: 28832621]

Hasin DS, Stinson FS, Ogburn E & Grant BF 2007 Prevalence, correlates, disability, and comorbidity of DSM-IV alcohol abuse and dependence in the United States: results from the National Epidemiologic Survey on Alcohol and Related Conditions. Archives of general psychiatry, 64, 830–842. [PubMed: 17606817]

Hughes JR, Keely J & Naud S 2004 Shape of the relapse curve and long-term abstinence among untreated smokers. Addiction, 99, 29–38. [PubMed: 14678060]

Jamal A, Homa DM, O'connor E, Babb SD, Caraballo RS, Singh T, Hu SS & King BA 2015 Current cigarette smoking among adults—United States, 2005–2014. MMWR Morb Mortal Wkly Rep, 64, 1233–1240. [PubMed: 26562061]

Kahler CW, Borland R, Hyland A, Mckee SA, Thompson ME & Cummings KM 2009 Alcohol consumption and quitting smoking in the International Tobacco Control (ITC) Four Country Survey. Drug and alcohol dependence, 100, 214–220. [PubMed: 19056188]

Kahler CW, Spillane NS & Metrik J 2010 Alcohol use and initial smoking lapses among heavy drinkers in smoking cessation treatment. Nicotine & Tobacco Research, ntq083.

Kahler CW, Strong DR, Papandonatos GD, Colby SM, Clark MA, Boergers J, Niaura R, Abrams DB & Buka SL 2008 Cigarette smoking and the lifetime alcohol involvement continuum. Drug and alcohol dependence, 93, 111–120. [PubMed: 17964082]

Kessler RC, Chiu WT, Demler O & Walters EE 2005 Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. Archives of general psychiatry, 62, 617–627. [PubMed: 15939839]

Krippendorff K 2012 Content analysis: An introduction to its methodology, Sage.

Lê Cook B, Wayne GF, Kafali EN, Liu Z, Shu C & Flores M 2014 Trends in smoking among adults with mental illness and association between mental health treatment and smoking cessation. Jama, 311, 172–182. [PubMed: 24399556]

Le Strat Y, Ramoz N & Gorwood P 2010 In alcohol-dependent drinkers, what does the presence of nicotine dependence tell us about psychiatric and addictive disorders comorbidity? Alcohol & Alcoholism, 45, 167–172. [PubMed: 20089545]

Ma J, Siegel RL, Jacobs EJ & Jemal A 2018 Smoking-attributable Mortality by State in 2014, US. American journal of preventive medicine, 54, 661–670. [PubMed: 29551325]

Milward J, Drummond C, Fincham-Campbell S & Deluca P 2018 What makes online substance-use interventions engaging? A systematic review and narrative synthesis. DIGITAL HEALTH, 4, 2055207617743354. [PubMed: 29942622]

Piasecki TM 2006 Relapse to smoking. Clinical psychology review, 26, 196–215. [PubMed: 16352382]

Rostron BL, Chang CM & Pechacek TF 2014 Estimation of cigarette smoking–attributable morbidity in the United States. JAMA internal medicine, 174, 1922–1928. [PubMed: 25317719]

Sas Institute, I., , 2017. (2017). SAS/STAT User's Guide (Version 14.1). Cary, NC: SAS Institute, Inc. .

Sells JR, Waters AJ & Maclean RR 2017 Evaluating the influence of at-risk alcohol use on factors associated with smoking cessation: Combining laboratory and ecological momentary assessment. Drug & Alcohol Dependence, 179, 267–270. [PubMed: 28822262]

Siegel R & Jemal A 2015 Cancer facts & figures 2015. American Cancer Society. Cancer Facts & Figures.

Talati A, Keyes K & Hasin D 2016 Changing relationships between smoking and psychiatric disorders across twentieth century birth cohorts: clinical and research implications. Molecular psychiatry.

Taylor GM, Dalili MN, Semwal M, Civljak M, Sheikh A & Car J 2017 Internet-based interventions for smoking cessation. The Cochrane Library.

Urbanoski K, Van Mierlo T & Cunningham J 2017 Investigating patterns of participation in an online support group for problem drinking: a social network analysis. International journal of behavioral medicine, 24, 703–712. [PubMed: 27549786]

Wang X, Zhao K & Street N 2014 Social support and user engagement in online health communities Smart Health. Springer.

Weinberger AH, Gbedemah M & Goodwin RD 2017 Cigarette smoking quit rates among adults with and without alcohol use disorders and heavy alcohol use, 2002–2015: A representative sample of the United States population. Drug and alcohol dependence, 180, 204–207. [PubMed: 28918239]

Zhao K, Wang X, Cha S, Cohn AM, Papandonatos G, Amato MS, Pearson JL & Graham A 2016 A multi-relational social network analysis of an online community for smoking cessation. Journal of medical Internet research, 18, e233. [PubMed: 27562640]

Table 1.

Ten topics about alcohol use and their associated words extracted from 6,059 alcohol-related posts using Correlated Topic Modeling (CTM).

Topic	Keywords	Prevalence (modal)	Prevalence (mean)
1	oil acid cup extract sauce pepper ethyl add cook minute white salt cheese tablespoon juice	2%	2%
2	smoke day feel time work night good today make thing think cigarette week smell start	16%	21%
3	nicotine addiction smoke brain addict relapse drug crave cigarette quit time dopamine mind recovery year	2%	3%
4	quit smoke drink day time year make alcohol life cigarette people thing give friend read	50%	43%
5	smoke feel body eat quit weight people time nicotine depression make food week withdrawal avoid	4%	4%
6	smoke tobacco cigarette smoker people health lung cancer make year time product study nicotine risk	3%	3%
7	back make time car thing leave call home put long tell year drive work day	6%	5%
8	game god year love Jesus amen leave day nicotine make team play time life home	2%	2%
9	day beer love drink good great train today friend party freedom bar celebrate lol back	15%	14%
10	dad stick mom care drink thing candy good kind love drive time bite head march	0%	13%

Table 2.

Topic Labels and representative posts for each of the three most prevalent alcohol-related topics (prevalence of each topic ≥ 10%).

Topic	Post	Excerpts from representative posts	γ
2: Cravings and Temptations around Alcohol	1	Day 58! Day 55 was tough. I went out with friends to a place where I would usually smoke outside of her apartment or on the walk to the bar and then outside of the bar…	0.94
	2	Yesterday was day 50 for me….it was extremely emotional one for me… Felt sick until I woke up from my nap and I felt better. Went to a neighbors for a little to let them know I am great…..they were all smoking and drinking…. I am not sure why I didn't relapse….	0.90
	3	… I'm having a really hard time today though the cravings are manageable at the moment but the further the day progresses the more anxiety is building and the more intense the cravings get… We usually sit on our front porch and smoke and drink our wine and chat with our smoker neighbor, and then go watch a movie and come out for smoke breaks every 30–60min.	0.89
4: Similarities of Nicotine Addiction to Alcoholism	4	Welcome to EX! You have found the AA for smoking. We will be here with you through your quit. I too smoked through everything in my life and depended on it in times of stress. I thought it calmed me down. But really it was just giving me the nicotine that I was addicted to. My fix. It only calmed down the addiction cravings and now that I don't smoke I don't have those cravings any more.	0.95
	5	I quit 77 days ago after 32+ years of smoking and several failed attempts to quit in the past. The difference this time is I have had enough. … We are all addicted to nicotine just as an alcoholic is addicted to drinking. When they kick the habit, just one drink will knock them right off the wagon again. The same goes for us.	0.95
	6	There was a time when i hated my life and everything around me, then I started self-talking. … I used alcohol as a crutch and thought it helped me deal with the unhappiness, but it only made matters worse. … After quitting drinking, and now smoking I`ve learned to be honest with myself and change my negative way of thinking.	0.94
9: Alcohol for Celebrations	7	Good morning fellow Freedom Riders! I am boarding the Train with 1575 Days of Freedom behind me! … I going to sit by this open window and enjoy the view until afternoon! Then I am going back to the dining car and get a big plate of hot wings and some cold beer! come and join me!!	0.96
	8	Hey [*username*]!!!! Rocking Train with some big hitters!!!! Can't have ice cream….but I'll take a glass of red wine! HUGE congrats [*username*], at 2700 days, you truly are an inspiration! … [*username*] on 1200 days and to [*username*] on 500 days!!! Love ya all! Treat yourselves to something wonderful!	0.95
	9	HUGE congratulations to [*username*] with 50 days, [*username*] with 60 days aaaaannnd….(drum roll, please) [*username*] WITH 100 DAYS!!!! The Triple Digit Club welcomes you with open arms and a nice cold beer, my friend! We are so proud of you!	0.95

Table 3.

Distribution of posts coded for negative sentiment about alcohol use during a quit attempt across the three most prevalent alcohol-related topics.

	Negative Sentiment (1,725 posts)		Non-Negative Sentiment (3,270 posts)	
Topic	**%**	**# posts**	**%**	**# posts**
2: Cravings and Temptations around Alcohol	36.2	357	63.8	630
4: Similarities of Nicotine Addiction and Alcoholism	36.0	1,106	64.0	1,963
9: Alcohol for Celebrations	27.9	262	72.1	677

Note. Posts assigned to their most likely topic (modal allocation). Row percents add to 100. The proportion of posts indicating negative sentiment differed by topic ($p < 0.001$)

Table 4.

Proportions of posts organized by topic and low, medium, and high in-degree and out-degree.

Topic	In-degree Low	In-degree Medium	In-degree High	p-value
2: Cravings and Temptations around Alcohol	26.4%	24.7%	10.6%	< 0.001
4: Similarities of Nicotine Addiction and Alcoholism	54.8%	50.2%	49.9%	0.036
9: Alcohol for Celebrations	4.7%	10.2%	20.1%	< 0.001
	Out-degree			
	Low	**Medium**	**High**	**p-value**
2: Cravings and Temptations around Alcohol	28.2%	19.1%	9.4%	< 0.001
4: Similarities of Nicotine Addiction and Alcoholism	53.3%	52.2%	49.1%	0.913
9: Alcohol for Celebrations	5.6%	13.2%	20.8%	< 0.001

Note. P-values compare differences across the three groups in the proportion of posts in each topic. Posts assigned to their most likely topic (modal allocation).