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Exploring the Social Structure of a Health-Related Online Community for Tobacco Cessation: A Two-Mode Network Approach

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Abstract

Unhealthy behaviors, such as tobacco use, increase individual health risk while also creating a global economic burden on the healthcare system. Social ties have been seen as an important, yet complex factor, to sustain abstinence from these modifiable risk behaviors. However, the underlying social mechanisms are still opaque and poorly understood. Digital health communities provide opportunities to understand social dependencies of behavior change because peer interactions in these platforms are digitized. In this paper, we present a novel approach that integrates theories of behavior change and Exponential Random Graph Models (ERGMs) to understand structural dependencies between users of an online community and the behavior change techniques that are manifested in their communication using an affiliation network. Results indicate population specific traits in terms of individuals' engagement in peer communication embed behavior change techniques in online social settings. Implications for personalized health promotion technologies are discussed.

Keywords

Health Communities; Social networks; Tobacco cessation

Introduction and Background

According to the World Health Organization (WHO), tobacco use is one of the leading causes of preventable death, causing over seven million deaths worldwide annually. Further exposure to second-hand smoke alone leads to 600,000 deaths. Tobacco use causes various chronic conditions such as cancer, heart disease, stroke, lung diseases, diabetes and Chronic Obstructive Pulmonary Disease (COPD), which collectively account for an estimated \$1.7 trillion a year leading to an economic burden on the global healthcare system [1]. Several

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interventions have been suggested and implemented to address tobacco use around the world – use of behavior counseling and nicotine replacement therapy [2]. Despite ongoing public health campaigns, tobacco use rates are still concerning. It is imperative for us to uncover mechanisms of behavior change to design scalable interventions that support cessation [3].

Studies indicate that social support and networks can have complex relationships with health behaviors and health outcomes [4]. For example, being married to a non-smoker and having a lower number of non-smokers in one's social network are associated with greater rates of smoking cessation. Christakis and Fowler demonstrated that quit attempts occurred within social clusters and that a variety of network variables were predictive of cessation, including the smoking cessation of a spouse, sibling, friend and co-worker [5]. Researchers have investigated these effects through a multitude of methods grounded in socio-behavioral theories and network science methods [3,6]. However, our understanding of the network dynamics of behavior change is still developing.

Advances in information and communication technologies have revolutionized the way in which individuals seek peer support to adopt and sustain positive health behaviors. Social media platforms have increasingly been used as behavior change venues where users reach out to their peers for support and guidance [7]. Analysis of peer interactions in these digital platforms can provide us with a deeper understanding of how social influence impacts users to quit tobacco use and stay abstinent. Consequently, this has raised interest in understanding how users of these platforms communicate with one another about health behavior change in these supportive settings. In this vein, previous work has primarily employed methods of content analysis including qualitative analysis [6], automated text analysis [8] and simulation-based effects [9] which enable identification of communication topics that could be linked to theoretical constructs and behavioral outcomes like abstinence and relapse rates. Although insightful, the problem with these approaches is that they remain agnostic to the structure of relationships that underlies the communication environment and interdependent nature of communicative choices [7]. For example, what one talks about the characteristics of those users, and their ongoing patterns of interaction is rarely integrated [6].

More recently, advances in social media analytics and social network modeling provide opportunities to extract the relational infrastructure of online communication forums like those supporting healthy behavior change, to uncover the social processes that bring structure to that communication, and to account for the interdependencies in those data. In this paper, we draw on these techniques to examine QuitNet, an online community for tobacco cessation. We conceptualize this environment as a bipartite (or two-mode) network, comprised of two sets of nodes—QuitNet users and the behavior change techniques they adopt and talk about in their communication threads—with edges between node sets representing a technique adoption tie. Then, using a class of statistical network models, the exponential random graph models (ERGMs), we investigate the degree to which the attributes of QuitNet users, namely their gender and age, organize the structure of their communication behavior change techniques. Findings from this analysis will reveal patterns of engagement with behavior change techniques that constitute online support structures for community members in online settings.

Methods and Materials

Data Site and Sample

QuitNet is a social media platform designed to help people quit smoking through peer support and pragmatic engagement. It is one of the first online social networks for health behavior change and has been in continuous existence since 1995 [10]. QuitNet offers various forms of social support. Users communicate with their peers in one of the following ways – one to many messages in threaded forums, through synchronous channels such as chat rooms or through asynchronous channels (e.g., private internal e-mail). Previous studies show that participation in QuitNet is associated with abstinence [3]. The primary mode of communication is through forum interactions. For the purpose of this study, we examined communication of 126 highly engaged QuitNet users in 2014 and 2015. In total, these 126 users exchanged 17,451 messages. This research project was reviewed and exempted by the Institutional Review Board at the University of Texas Health Science Center at Houston.

Qualitative Analysis

Two independent researchers coded 900 messages from this dataset, selected at random using the taxonomy of behavior change techniques (BCT taxonomy) [11] to ensure objectivity of the coding process and identify theoretical manifestations in QuitNet interactions. We used Cohen's Kappa to measure interrater reliability of the qualitative coding. The BCT taxonomy consists of 93 theory-linked techniques grouped into 16 classes. A single behavior change technique can be related to similar behavior change processes from multiple behavior change theories such as the Health Belief Model, Transtheoretical Model, Social Cognitive Theory and Social Change Theory [12]. Each message was coded appropriately to one or more techniques that were linked to a particular behavior (for example, smoking), focusing on a particular population (for example, QuitNet users). The definition of each technique can be found in [11] with illustrative examples.

Automated Classification System

Using methods from distributional semantics and machine learning, we developed an automated classification system to scale up the BCT annotation to the remaining messages in the dataset. To generate vector representations of messages, we used neural word embeddings, specifically the Skipgram-with-Negative-Sampling (SGNS) algorithm developed by Mikolov and colleagues [13], as implemented in the open source semantic vectors [14] package for distributional semantics. Additionally, Wikipedia was used as a background corpus. Our Wikipedia corpus contains 1.9 billion words in more than 4.4 million articles, and 500-dimensional Wikipedia-derived term vectors were obtained by applying the SGNS algorithm to the Wikipedia background corpus. This decision was motivated in part by the terse nature of the messages exchanged in QuitNet user forums, which often do not provide enough contextual information to train a distributional model [6, 8, 15]. We first superposed (added together) the Wikipedia term vectors for the terms that occur in each QuitNet message to obtain Wikipedia-based QuitNet message vectors. We then composed term vectors for the terms that occur in QuitNet by adding QuitNet message vectors for each message in which a given term in QuitNet occurred. As such, these term vectors encode distributional information from Wikipedia and from QuitNet-specific

contextual use of terms. Finally, QuitNet message vectors were generated by superposing these term vectors. The components of the vectors generated in this way were used as feature vectors for supervised machine learning that was conducted using the widely used Waikato Environment for Knowledge Analysis (WEKA) open source package for machine learning [16]. Each of the techniques of behavior change taxonomy was used as a target for classification. We used only eight techniques due to sparse representation in qualitative coding. Ten-fold cross validation was applied using the random forest classifier to evaluate a binary classifier for each of the themes. Each of the trained validated classification models was then used to classify the entire dataset.

Two-Mode Network Analysis

We dichotomized the messages exchanged by a QuitNet user based on whether or not the message is assigned a specific behavior change technique during our text analysis (presence of a technique: 1, else: 0). From this, we were able to create a user to behavior change technique, binary network.

Data were thus analyzed using two-mode network analysis by creating an affiliation network composed of two sets (or nodes) of actors – users of the QuitNet platform (N=126) and the BCT techniques embedded in their QuitNet posts (N=8). Ties are defined only between members of each set but not within sets of nodes [17]. For this reason, the network is comprised only of user-to-technique ties; ties connecting QuitNet users to one another or ties connecting behavior change techniques to one another are not explored.

We then used a class of statistical models for social networks called Exponential Random Graph Models (ERGMs) [18, 19], which allow us to account for the interdependencies in mentions of behavior change techniques among users of the same platform. ERGMs have been applied to a wide array of fields as diverse as epidemiology [20], political science [21], communication studies [22], biological sciences [23] and archeology [24]. As described in previously published work [25], ERGMs permit inferences about how network connections emerge by estimating the likelihood of a tie being present (or absent) in the network as a function of small local tie-based configurations (or patterns). Each configuration represents a distinct social process, such as reciprocity or balance, and corresponds to a specific parameter in the model. From this perspective, ERGMs adopt a logic similar to logistic regression, in which a binary outcome like the adoption of behavior (or the presence of a tie in ERGMs) is modeled as a function of selected, predictor variables (or local configurations in ERGMs) that are thought to explain the observed outcome. The configurations modeled in ERGMs can emerge from endogenous processes – i.e., when actors form ties in response to the other ties being made in their social environment (e.g., when frequently mentioned behavior change techniques continue to be mentioned by more QuitNet users) or in response to exogenous properties that exist outside the network like the attributes of other QuitNet users (e.g., when male QuitNet users tend to adopt the same behavior change techniques).

In statistical terms, the effect of each parameter is estimated by determining the prevalence of the modeled configurations in the observed network and then assessing their statistical likelihood above what would occur by chance alone [19]. A parameter estimate that is

positive and significant indicates that ties are more likely to occur within the configuration tested than by chance alone. Conversely, parameter estimates that are negative and significant suggest that ties are less likely to occur within the configuration tested than by chance alone. ERGMs are deemed acceptable when the parameters converge, which occurs when the convergence t-ratios for each parameter reaches <0.10 . Details about the specification, estimation, and simulation of ERGMs can be found here [26, 27].

Selecting which parameters to be included in an ERGM should be grounded in which distinct theories of interaction one wants to test or the research questions one wants to explore. Given that the focus of this analysis centers on the relationship between demographic attributes of QuitNet users and their patterns of communication about behavior change techniques, our estimation focuses on the effects of five attribute-based parameters to determine whether they were more likely to occur than expected by chance alone. Figure 1 illustrates the corresponding configurations of these effects.

First, to account for endogenous aspects of network emergence, we include two purely structural (or non-attribute) effects. The endogenous edge parameter (Figure 1a) is a required parameter and represents the overall propensity for QuitNet users to mention behavior change techniques in their posts. We also included the Alternating K-star parameter (Figure 1b), which represents the tendency for QuitNet users to mention multiple behavior change techniques and, therefore, corresponds to the variance in the distribution of technique mentions among QuitNet users.

With respect to our main interest -- attribute-based effects -- we parameterize several configurations that test the effects of gender and age on QuitNet users' patterns of communication about behavior change techniques. Specifically, we include parameters that represent the likelihood of male QuitNet users mentioning a behavior change technique (Figure 1c), the likelihood of male QuitNet users mentioning multiple behavior change techniques (Figure 1d), the likelihood of male QuitNet users mentioning the same behavior change technique (Figure 1e), the likelihood of older QuitNet users mentioning a behavior change technique (Figure 1f), and the likelihood of older QuitNet users mentioning multiple behavior change techniques (Figure 1g). Modeling results were implemented using MPNet, a network estimation program designed for one-mode, two-mode and multilevel network data [17–18].

Results

Qualitative Analysis

Table 1 provides sample QuitNet messages and the BCT techniques (and their definitions) assigned to them during manual coding. Of the manually coded messages, 32% were related to feedback and monitoring, 29% were related to social support, 21% were goals and planning, followed by rewards, natural consequences, associations, self belief and comparison of behavior and outcomes, repetition, and substitution.

Automated Classification System

Due to insufficient positive examples in the training set, we disregarded eight of the 16 techniques of the taxonomy for final classification. For the remaining eight techniques, the precision, recall, and f-measure using Random forest classifier were 0.76, 0.74, and 0.78, respectively. The themes considered for further analysis were goals and planning, feedback and monitoring, social support, natural consequences, comparison of behavior, comparison of outcomes, rewards and threat, and self-belief. Based on the automated classification, we found that each of the users exchanged messages that embedded at least one behavior change technique and up to eight techniques. On average from the full sample, we see that far fewer users (13%) mention goals and planning, 55% of the users mention outcomes, 27% mention comparison of behavior, 53% users mention feedback and monitoring, 32% users mention natural consequence, self belief is mentioned by 33% of the users and social support is mentioned by 37% of users and finally 46% of users mention reward and threat. Table 2 shows the frequencies of each behavior change technique. Among the 126 users, 36 (29%) are men and 90 (71%) are women.

The bias towards females in the sample is a result of the inherent skewness in the utility of online social interventions such as QuitNet [6]. In the comparison of means tests not shown here, we find no significant differences between men and women with respect to the types of behavior change techniques they mention in their posts.

Figure 2. illustrates the two-mode affiliation network of 126 QuitNet users and eight behavior change techniques. QuitNet users are depicted as circles and the techniques are depicted as squares. The BCT technique nodes (squares) are sized by the number of mentions they received. Between node sets, there are a total of 375 ties, representing users' mentions of behavior change techniques in their QuitNet posts. Users mentioned on average 2.98 behavior change techniques and each technique had on average 46.88 mentions.

Exponential Random Graph Model (ERGM)

Results of the two-mode ERGM are shown in Table 3. Reported in this table are parameter estimates, standard errors, and t-ratios, which reveal parameter convergence ($t < 0.1$). The maximum likelihood (ML) estimate for a parameter indicates the direction of its propensity above what would be expected by chance alone. The significance is achieved when the ML estimate is greater than twice the SE.

Two-Mode Structural Effects

Here, the model estimates the effects of two structural or non-attribute parameters, which represent local structural patterns in the QuitNet user affiliation network. The required Edge parameter is negative, indicating that QuitNet users are less likely than expected to affiliate with behavior change techniques (ML Estimate = -0.26, SE = 1.01). This reinforces the low density of the user affiliation network and suggests that adopting behavior change techniques is not random or haphazard. The negative estimate of alternating K-star parameter suggests that the likelihood of a user affiliating with multiple techniques is less likely than expected by chance (ML = -0.30, SE = -0.59).

Attribute - Based Edge Effects

The first attribute-based parameter, Gender density, is negative and significant (ML Estimate=-1.23, SE=0.60) indicating that men are less likely to adopt a behavior change technique than expected by chance. The attribute-based edge parameter for users' age (ML Estimate=0.004, SE=0.01) is positive indicating that older people are likely to adopt behavior change techniques. However, the effect is not significant. The gender-based expansiveness parameter estimate is not significant (ML Estimate=-0.09, SE=0.20), suggesting that men are no more or less likely than expected by chance to adopt multiple behavior change techniques. The gender homophily parameter estimate is positive and significant (ML Estimate=0.10, SE=0.02), indicating that men are more likely than expected by chance to adopt the same techniques. Finally, age-based expansiveness, which represents the likelihood that older QuitNet users are more likely to adopt multiple techniques is not significant (ML Estimate=0.0001, SE=0.003).

Discussion

Given that people increasingly turn to online social environments to find community and support, an opportunity arises to employ these platforms in health behavior interventions. Adopting a two-mode network analytic approach, we used a class of stochastic models called exponential random graph models (ERGMs) to determine the ways in which attributes of community users structure their communicative interactions about behavior change. Descriptively, we found that users more often discussed techniques that fell into the *Comparison of Outcomes, Feedback & Monitoring*, and *Reward & Threat* categories of behavior change. This finding can inform future interventions the need for a more adaptive and personalized, technology driven interventions such as a mobile app that includes effective quit plans, use of novel machine learning algorithms based on feature selection to obtain high classification rates to predict relapse (for e.g., smoking urges) and population-level interventions focusing on health effects of tobacco use.

A strength of this study lies in its analytic approach. Standard regression models are designed for data where independence among observations can be assumed. However, in a networked and open online forum like QuitNet, where users observe and respond to what others are posting about, we cannot assume that observation of what one user communicates about is independent of what others are talking about in those spaces. As such, an approach was needed that could account for those dependencies. To this end, we drew on the exponential random graph model (ERGM), which allows us to see how characteristics of QuitNet users condition their interactions and communication about behavior change techniques. The utility of automated text analysis approaches has allowed us to bridge two threads of socio-behavioral science driven by theoretical constructs and network models. Findings from our analysis provide insights about the underlying social dynamics of behavioral choices (e.g., adopting a behavior change technique) that would otherwise go undetected using standard regression models. These insights provide health researchers and interventionists with new directions for designing network based behavioral interventions [28] that target the social dynamics of behaviors like abstinence from tobacco use.

Our study has several limitations. Firstly, because these data are cross-sectional, inferences about cause and effect cannot be made. Secondly, our sample is limited to only those users who are highly engaged during 2014-2015. Moving forward, we should adopt the proposed techniques to identify patterns of relapse and quit sustenance. In addition, the accuracy of the automated system can further be improved through the use of advanced word representations [29, 30].

Conclusion

Tobacco use causes seven million deaths around the world each year. New modes of nicotine intake (JUULS, e-cigs) are now considered safer than traditional cigarettes and misinformation is quite prevalent regarding these topics. In this new media environment, adaptive social interventions to help people abstain from tobacco use is a high-priority task. The major contribution of this study is its employment of integrative analytical framework to elucidate the structural dependencies between community users and their communication attributes. Insights from this work allow implementation of targeted, recommendation engines to promote meaningful affiliations with content and social ties based on user characteristics. Such translation can set the stage for scalable network-based interventions that can enable individuals and communities to engage in positive health behaviors.

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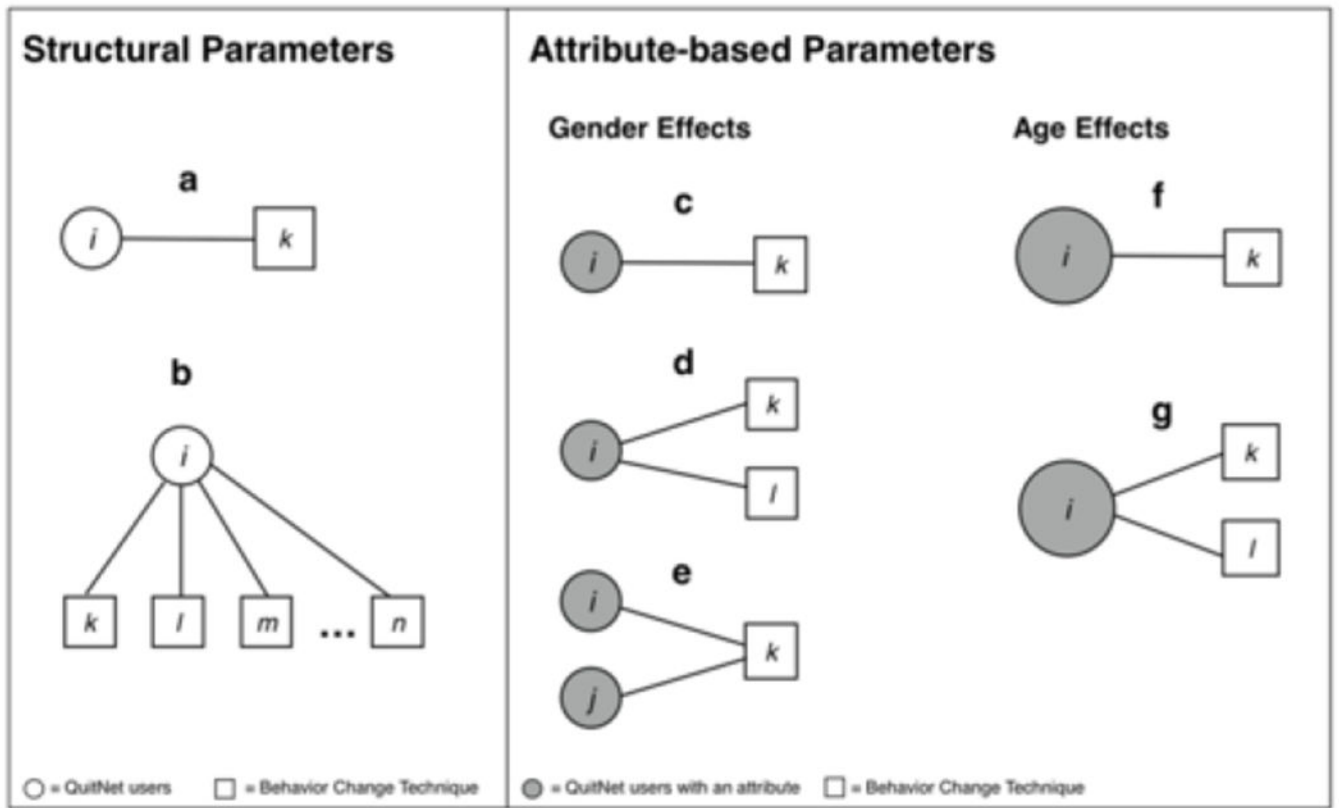


Figure 1. Parameterized Local Configurations among QuitNet Users a and j and Behavior Change Techniques k, l, m, and n. The parameters represent the following processes: (a) the likelihood of QuitNet users mentioning a behavior change technique, (b) the likelihood of QuitNet users mentioning multiple behavior change techniques, (c) the likelihood of male QuitNet users mentioning a behavior change technique, (d) the likelihood of male QuitNet users mentioning multiple behavior change techniques, (e) the likelihood of male QuitNet users mentioning the same behavior change technique, (f) the likelihood of older QuitNet users mentioning a behavior change technique, and (g) the likelihood of older QuitNet users mentioning multiple behavior change techniques.



Figure 2. The network structure of mentions of behavior change techniques among 126 members of QuitNet as a 2-mode cessation technique affiliation network: 2014 and 2015.

Table 1.

Illustration of QuitNet Messages and Assigned Behavior Change Technique

Quit message	Assigned technique
To tell you the truth, it's a new experience for me NOT to cough (I smoked for 38 or so years - YUK!). Good luck to you.	Natural consequences
Wow!!! xyxx is correct. You control your attitude. Deep breathing, chew gum, take a walk (or maybe a hike:-) Hang in there. This is not easy, your an addict.	Repetition and substitution
At this point in your Quit it may be best to look at more immediate gains such as money saved or improved self esteem or better health. My dollar savings are \$5,293 and that is real and for now. My life saved is an unrealized 15 weeks and 20 minutes that may never happen.	Comparison of outcomes

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Table 2.

Descriptive Statistics of Users and the Behavior Change Techniques within the QuitNet Forum

Behavior Change Techniques	Full user Sample (N=126)	Men (N=36)	Women (N=90)
Outcomes	70(55)	22(61)	48(53)
Feedback and monitoring	67(53)	19(53)	48(53)
Reward and threat	58(46)	17(47)	41(45)
Social support	47(37)	15(42)	32(35)
Self belief	42(33)	10(28)	32(35)
Natural consequence	40(32)	10(28)	30(33)
Comparison of behavior	34(27)	5(14)	29(32)
Goals and planning	17(13)	3(8)	14(15)

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Table 3.

Exponential Random Graph Model of 2-Mode QuitNet User Affiliation Network with Behavior Change Techniques with Gender Modeled as Covariates

Parameter	ML Estimate	Standard Error(SE)	t-ratio
2-mode structure			
Edge density	-0.26	1.01	-0.01
Alternating k-star	-0.3	0.6	-0.02
User attribute-based edges			
Gender edge density	-1.23*	0.6	-0.02
Age edge density	0.004	0.01	-0.02
Gender based expansiveness	-0.09	0.2	-0.04
Gender homophily	0.10*	0.01	0.01
Age based expansiveness	0.0001	0.003	-0.04

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