Social Dynamics of Substance Use in Online Social Networks for Smoking Cessation

Amanda L. Graham, PhD
Director, Research Development
Schroeder Institute for Tobacco Research & Policy Studies

Professor of Oncology (Adjunct)
Georgetown University/Lombardi Comprehensive Cancer Center
Funding

- National Cancer Institute #R01CA192345-01 (Graham, PI, Zhao, Co-PI)
  - Sept 1, 2014 – Aug 30, 2017
- RFA-CA-14-008: Using Social Media to Understand and Address Substance Use and Addiction (R01)
  - Collaborative Research on Addiction (CRAN) Initiative
Disclosures

- As of Dec 2014, I lead the management and development of BecomeAnEX.org, the online social network for smoking cessation that is the focus of these analyses.

- Consultant to Epidemico on FDA BAA-13-00119, *Enhancing tobacco surveillance through online monitoring.*
Overview

- Evidence linking online social networks and smoking cessation
- Methodological challenges
- Aims of our project
- Social computing methods
- Early findings (illustrative)
Online Social Network = ?

Table 1. Examples of Open and Intentionally Designed Online Social Networks

<table>
<thead>
<tr>
<th>Types of Online Networks</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open social networks</td>
<td>Facebook, Twitter, Google+</td>
</tr>
<tr>
<td>Intentionally designed social networks</td>
<td>The Healthy Lifestyle Network, QuitNet, PatientsLikeMe, BecomeAnEX</td>
</tr>
</tbody>
</table>


Reach of Online Social Networks for Cessation

- Social media and Web 2.0 applications now common in web-based smoking cessation programs
  - Quitlines in 29 U.S. states
  - Commercial programs

REF: http://map.naquitline.org/reports/web/
Online Social Networks & Abstinence

Smoking outcomes at 3 months

- 7-day abstinence: OR=3.24, 95% CI 1.76–5.93
- Continuous abstinence for 2+ months: OR=4.03, 95% CI 2.10–7.72
- Baseline motivation not significant in model

Table 2. Median (interquartile range) of QuitNet utilization among quitters and smokers

<table>
<thead>
<tr>
<th></th>
<th>Quitters (n=67)</th>
<th>Smokers (n=156)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of logins</td>
<td>9 (1–42)</td>
<td>2 (1–5)***</td>
</tr>
<tr>
<td>Average session length in minutes</td>
<td>12 (7–20)</td>
<td>14.5 (8–23) ***</td>
</tr>
<tr>
<td>Total number of minutes online</td>
<td>103 (33–339)</td>
<td>33 (17–82.5) ***</td>
</tr>
<tr>
<td>Total number of pages viewed</td>
<td>128 (31–366)</td>
<td>34 (17–87)***</td>
</tr>
<tr>
<td>Percentage posting at least one time in public forums</td>
<td>19.4</td>
<td>4.5***</td>
</tr>
<tr>
<td>Percentage with at least one buddy</td>
<td>19.4</td>
<td>9.6</td>
</tr>
<tr>
<td>Percentage who sent Qmail to at least one person</td>
<td>25.4</td>
<td>9.0**</td>
</tr>
<tr>
<td>Percentage who received Qmail from at least one person</td>
<td>41.8</td>
<td>20.5***</td>
</tr>
</tbody>
</table>

Note. Between-group differences were analyzed using Wilcoxon W test for continuous data (median) and chi-square (proportions). *p<.05; **p<.01; ***p<.001.

### Table 3. Association between website usage and quit behavior over time using generalized estimating equations (GEE).

<table>
<thead>
<tr>
<th>Regression models</th>
<th>Quit attempts OR (95% CI)</th>
<th>P</th>
<th>7-Day abstinence OR (95% CI)</th>
<th>P</th>
<th>30-Day abstinence OR (95% CI)</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visits to the website<strong>b</strong></td>
<td>1.09 (0.94-1.28)</td>
<td>.26</td>
<td>2.04 (1.75-2.39)</td>
<td>&lt;.001</td>
<td>1.73 (1.47-2.05)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Model 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visits to the website<strong>b</strong></td>
<td>1.10 (0.88-1.38)</td>
<td>.39</td>
<td>1.55 (1.26-1.91)</td>
<td>&lt;.001</td>
<td>1.36 (1.08-1.70)</td>
<td>.008</td>
</tr>
<tr>
<td><strong>Use of Community feature</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 vs 0 times</td>
<td>0.79 (0.53-1.17)</td>
<td>.24</td>
<td>1.74 (1.13-2.67)</td>
<td>.01</td>
<td>1.37 (0.81-2.30)</td>
<td>.24</td>
</tr>
<tr>
<td>≥2 vs 0 times</td>
<td>1.06 (0.62-1.83)</td>
<td>.82</td>
<td>2.22 (1.34-3.69)</td>
<td>.002</td>
<td>2.42 (1.35-4.34)</td>
<td>.003</td>
</tr>
</tbody>
</table>

---

*a* All models adjusted for demographics, nicotine dependence, baseline quit attempts, peer smoking, household smoking, motivation to quit, positive and negative social support, health status, advice to quit from a health care provider, use of at least one cessation aide, baseline depression, baseline perceived stress, having a partner who smokes, and frequency of use of the Internet. Model 1 includes all covariates plus visits to the website. Model 2 includes all covariates, visits to the website, and use of specific BecomeAnEX.org features.

*b* Represented as the log of total visits to the BecomeAnEX.org website over the study period.

---

Online intervention engagement predicts smoking cessation

Ralf Schwarzer a,b,*, Lars Satow a

a Freie Universität Berlin, Germany
b Warsaw School of Social Sciences and Humanities, Poland

Fig. 2. Maintenance of non-smoking in those who composed their personal bulletin board entry as compared to those who did not contribute (Germany, 2011).

Fig. 4. Maintenance of non-smoking depending on the level of their virtual community activities (Germany, 2011).
Causality and Mechanisms Unclear

- Engagement in online social networks for cessation appears to be associated with abstinence

- Causality?

- May be misguided to randomize people to “form interpersonal relationships”
Social Dynamics of Substance Use in Online Social Networks for Smoking Cessation

R01CA192345-01

GOAL: To understand social network dynamics and the social processes that occur within online social networks for cessation.

- hone computational methods applied in other fields
- inform intervention design
Study Team

University Iowa
- Kang Zhao, PhD: Co-Principal Investigator
- Xi Wang, MS: Analyst/PhD Candidate

Schroeder Institute, Legacy
- Sarah Cha, MSPH: Project Manager
- Amy Cohn, PhD: Co-Investigator
- Jennifer Pearson, PhD: Co-Investigator

Brown University
- George Papandonatos, PhD: Biostatistician
- Bahar Erar, MS: Analyst/PhD Candidate

Beaconfire
- Miro Kresonja: Lead Software Engineer

BecomeAnEX.org
- Giulia Pagano: Site Member/Domain Expert
- Tommy Piver: Site Member/Domain Expert
- Sudie Dinofrio: Site Member/Domain Expert
Building a Transdisciplinary Collaboration

Understanding Topics and Sentiment in an Online Cancer Survivor Community

Kenneth Portier, Greta E. Greer, Lior Rokach, Nir Ofek, Yafei Wang, Prakhar Biyani, Mo Yu, Siddhartha Banerjee, Prasenjit Mitra, John Yen

Correspondence to: Kenneth M. Portier, PhD, Intramural Research Department, American Cancer Society Corporate Center, 250 Williams St NW, Atlanta, GA 30303 (e-mail: kenneth.portier@cancer.org).

Get Online Support, Feel Better—Sentiment Analysis and Dynamics in an Online Cancer Survivor Community

Baojun Qin¹, Kang Zhao¹, Prasenjit Mitra¹, Dinghao Wu¹, Cornelia Caragea¹, John Yen¹, Greta E. Greer¹, Kenneth Portier¹

¹Department of Computer Science and Engineering
²College of Information Sciences and Technology

The Pennsylvania State University, University Park, PA 16802
³American Cancer Society, Inc.
425 Williams Street NW, Atlanta, GA 30303

Finding influential users of online health communities: a new metric based on sentiment influence

Kang Zhao¹, John Yen², Greta Greer³, Baojun Qiu¹, Prasenjit Mitra², and Kenneth Portier³

¹Department of Management Sciences, The University of Iowa.
S224 PBB, Iowa City, IA 52242. kang-zhao@uiowa.edu.
Phone: (319) 335-3831. Fax: (319) 335-0297.

²College of Information Sciences and Technology, The Pennsylvania State University, University Park, PA 16802.

³American Cancer Society, 250 Williams Street NW, Atlanta, GA, 30303.

⁴eBay Inc. 2065 Hamilton Ave, San Jose, CA 95125.
Cigarette tracker
Identify triggers
Set quit date
Prepare for quitting
Preventing relapse

Content about Rx
Videos
Adherence

Online community
- Personal profile
- Blogs
- Group Discussions
- Wall Posts
- Private Messages

How EX Works:
The EX Plan is based on scientific research and practical advice from ex-smokers. It isn't just about quitting smoking. It's about 're-learning life without cigarettes'.

RE-LEARN HABIT
You know how certain things make you want to smoke? EX shows you how to handle them without reaching for a cigarette.

RE-LEARN ADDICTION
Nicotine changes your brain, so it's harder to quit. EX shows you how to fight back and double your chances for success.

RE-LEARN SUPPORT
The right kind of support can increase your chances of quitting. EX shows you how to get the support that will work for you.

Get Some Extra Help.
Our online community is filled with people who know what you're going through. Let them cheer you on.

Visit Community
Figure 1. Conceptual Model of how Online Social Networks Influence Smoking Behavior (adapted from Berkman, 2000)

- **Social Network Structure**
  - Network size
  - Density
  - Degree distributions
  - Structure
  - Assortativity

- **Characteristics of Network Ties**
  - Strength
  - Reciprocity
  - Transitivity

- **Characteristics of Individual Nodes**
  - Centrality

---

- **Social Engagement**
  - (social roles within network)

- **Social Influence**
  - (attitudes about cessation-related “hot topics”)

- **Social Support**
  - Instrumental Support
  - Emotional Support

- **Smoking/Quitting**
  - NRT
  - E-cigarettes
  - “Damsel in Distress”
  - “Troublesome Truck”
  - “Cheerleader”
  - “Arbitrator”
  - Varenicline/Chantix
  - Alcohol and drinking
  - Quitting cold turkey
  - “Crisis Manager”

---

- **BecomeAnEX.org**
  - 2008-2014
  - >676,000 users
  - 1.6 M posts

---

**DYNAMIC CHANGES OVER TIME**
Engagement Promotes Abstinence in a Web-based Cessation Intervention: Cohort Study

Amanda Richardson, MS, PhD; Amanda L Graham, PhD; Nathan Cobb, MD; Haijun Xiao, MS; Aaron Mushro, MS, MBA; David Abrams, PhD; Donna Vallone, MPH, PhD

Abstract

Background: Web-based smoking cessation interventions can have a public health impact by promoting cessation and can reach large numbers of smokers in a cost-efficient manner, but the effectiveness of such interventions has not been well studied. It is still unclear how such interventions promote cessation, who benefits, and how to improve them.

Objective: To examine the effectiveness of a highly promoted Web-based smoking cessation intervention over time, identify the most effective features, and understand who is most likely to benefit.

Methods: A sample of 1,033 new adult registrants was recruited from a Web-based automated study management system. Abstinence was assessed by self-report through telephone follow-up for nonrespondents at 1, 3, and 6 months. Generalized estimating equations (GEE) were used to examine predictors of website utilization at unweighted and weighted data.

Results: The 7-day point prevalence abstinence rates at 6 months ranged from 60.3% to 69.4% across intent-to-treat samples, respectively. Predictors of abstinence in unweighted analyses included active engagement in features such as the website and social network. In weighted analyses, only motivation to quit was a key predictor of website utilization, whereas negative affect and increasing visits to the site were not.

Conclusions: Engagement is critical to promoting smoking cessation. The next generation of Web-based smoking cessation interventions needs to maximize the initial engagement of all new visitors and work to retain those smokers who proceed to register on the site.

Improving adherence to web-based cessation programs: a randomized controlled trial study protocol

Amanda L Graham, Sarah Cha, George D Papandonatos, Nathan K Cobb, Aaron Mushro, Ye Fang, Raymond S Niura, and David B Abrams

Abstract

Methods/Design: This study compares the efficacy of a smoking cessation with free NRT and a social network (SN) protocol designed to integrate participants. Using a 2 (SN, no SN) x 2 (NRT, no NRT) randomized, controlled factorial design, 3 months, and 9 months, this study will recruit N = 4,000 new members. Randomize them to: 1) WEB, 2) WEB + SN, 3) WEB + NRT, or 4) WEB + SN + NRT interventions will outperform WEB and that WEB + SN + NRT will outperform point prevalence cessation at 9 months. Exploratory analyses will examine mediators and moderators of outcome.

Trial registration: ClinicalTrials.gov ID: NCT0127327

Keywords: Smoking cessation, Internet, Adherence, Social networks, Nicot

- N=5292 BecomeAnEX members
- RCT, 2x2 design (2012 – present)
- Follow-up 3, 9 months
- Response rates (ongoing): ~ 61.3% (3mo), 54.1% (9mo)
Primary Aim 1

Examine social network dynamics, sentiment dynamics, and social support as predictors of 3-month abstinence in the N=5,292 sample, and validate results in the N=1,033 sample.

*H1 (social network analyses)*: Greater exposure to abstinence norms via former smokers (i.e., centrality in more heterogeneous networks) predicts abstinence.

*H2 (text analytics)*: Greater exposure to social support predicts abstinence.

*H3 (sentiment analyses)*: Greater exposure to positive sentiment for proven quit methods (e.g., NRT) predicts higher abstinence rates, whereas greater exposure to positive sentiment about unproven methods (e.g., unassisted) predicts lower abstinence rates.
Primary Aim 2

Examine social network dynamics related to tobacco and alcohol use.

*H4:* Socially integrated drinkers will exert greater influence on sentiment dynamics about alcohol use than more isolated drinkers.

*H5:* Greater exposure to alcohol-related social support among drinkers predicts higher engagement with the site.
Exploratory Aim

Explore the correspondence between smoking status discerned from text analytics and 3-month outcomes to determine the feasibility of estimating quit rates in online social networks for cessation.
Computational methods for research in online health communities

Kang Zhao, PhD
Assistant Professor
Department of Management Sciences, Tippie College of Business
Interdisciplinary Graduate Program in Informatics
The University of Iowa
35% of U.S. adults have gone online for medical and health information; 24% also sought information or support from peers who have the same health condition.
Leverage the big data from social network/media

**WHO**

- Network Structures
  - Centrality analysis,
  - Community discovery,
  - Link prediction,

**WHEN**

- Temporal Dynamics
  - Network evolution,
  - Trajectory analysis,
  - Behavior adoption,

**WHAT**

- Text Mining
  - Content/behavior detection,
  - Topic modeling,
  - Sentiment analysis,

- Diffusion,
- Influence,
- Behavior change,
- Team performance,
...
Social network 101

• A social network consists of nodes and edges
  – Nodes represent individuals
  – Edges represent relationships
    • Friendship, kinship, colleague, ...
    • Edges can have directions
      – Directed edges: Twitter following, paper citation, ...
      – Undirected edges: Facebook friends, collaboration, ...

• Degree centrality
  – In undirected networks: total # of neighbors
  – In directed networks:
    • In-degree: # of incoming edges
    • Out-degree: # of outgoing edges
BecomeAnEX Data

5 years, 676.7k users, 1.5 million posts/messages, 6.2 million page views.
Social networks in BecomeAnEX

• Nodes:
  – Users of BecomeAnEX

• Edges:
  – Directed
  – Represent the flow of information/support via several communication channels (blog, comments, wall posts, group discussions, private message).
Basic statistics of the network

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. of nodes with degree &gt;0</td>
<td>58,941</td>
</tr>
<tr>
<td>Number of edges</td>
<td>1,466,643</td>
</tr>
<tr>
<td>% of reciprocated ties</td>
<td>25.36%</td>
</tr>
<tr>
<td>% of nodes in the LSCC</td>
<td>21.43%</td>
</tr>
<tr>
<td>Avg. shortest path length in LSCC</td>
<td>2.51</td>
</tr>
</tbody>
</table>

In-degree: how many other users have influenced/supported a user

Out-degree: how many other users a user has influenced/supported

LSCC (the largest strongly connected component) is the largest group of nodes, in which there is a possible path between every pair of nodes.
How can one’s network centrality and its temporal trend predict abstinence?

Preliminary results
  Increases in lurking activities is predictive of abstinence
  More details or this is enough??
A multi-relational perspective

• The network we analyzed aggregates users’ interactions across 4 ways of communication.
  – What if we build 4 subnetworks, each for one way of communication?
  – Each subnetwork has different structures

<table>
<thead>
<tr>
<th></th>
<th>Blog</th>
<th>Message Board</th>
<th>Group Discussion</th>
<th>Private Message</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. of nodes w/ degree &gt;0</td>
<td>14,807</td>
<td>23,702</td>
<td>11,882</td>
<td>33,330</td>
</tr>
<tr>
<td>Number of edges</td>
<td>649,207</td>
<td>819,531</td>
<td>257,237</td>
<td>55,380</td>
</tr>
<tr>
<td>% of reciprocated ties</td>
<td>34.34%</td>
<td>29.14%</td>
<td>4.42%</td>
<td>7.14%</td>
</tr>
<tr>
<td>% of nodes in the LSCC</td>
<td>59.53%</td>
<td>24.18%</td>
<td>25.83%</td>
<td>5.75%</td>
</tr>
<tr>
<td>Avg. shortest path length in LSCC</td>
<td>2.45</td>
<td>2.30</td>
<td>3.80</td>
<td>2.83</td>
</tr>
</tbody>
</table>
Similarity among subnetworks

- Structural similarity measured by edge overlap

<table>
<thead>
<tr>
<th>Subnetwork pairs</th>
<th>Edge overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blog vs Message Board</td>
<td>0.21</td>
</tr>
<tr>
<td>Blog vs Group Discussion</td>
<td>0.04</td>
</tr>
<tr>
<td>Message Board vs Group Discussion</td>
<td>0.04</td>
</tr>
<tr>
<td>Private Message vs Blog</td>
<td>0.02</td>
</tr>
<tr>
<td>Private Message vs Message Board</td>
<td>0.01</td>
</tr>
<tr>
<td>Private Message vs Group Discussion</td>
<td>0.01</td>
</tr>
</tbody>
</table>

- Similar results if we examine degree correlations.
## Co-evolution of the subnetworks

- After forming the 1\textsuperscript{st} tie in one subnetwork, what are the chances the two user form ties in the 2\textsuperscript{nd} or even 3\textsuperscript{rd} subnetworks?
  - Enabled by “When” data

<table>
<thead>
<tr>
<th>1\textsuperscript{st} tie</th>
<th>P(1\textsuperscript{st} tie)</th>
<th>P(forming 2\textsuperscript{nd} ties</th>
<th>1\textsuperscript{st})</th>
<th>Top sequence</th>
<th>P(forming 3\textsuperscript{rd} ties</th>
<th>1\textsuperscript{st})</th>
<th>Top sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blog</td>
<td>34.6%</td>
<td>28.7%</td>
<td>BL → MB</td>
<td>1.7%</td>
<td>BL → GD → MB</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Message Board</td>
<td>42.4%</td>
<td>13.1%</td>
<td>MB → BL</td>
<td>1.0%</td>
<td>MB → BL → GD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group Discussion</td>
<td>19.4%</td>
<td>11.6%</td>
<td>GD → MB</td>
<td>5.8%</td>
<td>GD → BL → MB</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private Message</td>
<td>3.8%</td>
<td>15.1%</td>
<td>PM → BL</td>
<td>12.7%</td>
<td>PM → BL → MB</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Text mining

• Automated analysis of large-scale text data
  – Does a post contain informational support?
  – Does a post contain positive sentiment?

• Our tasks
Next Steps & Future Directions

- Advance social network theory
- Understand network topology and social network processes
- Maximize population impact of Internet cessation interventions
Contact Info:

Amanda L. Graham, PhD
agraham@legacyforhealth.org

Kang Zhao, PhD
kang-zhao@uiowa.edu
References


