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

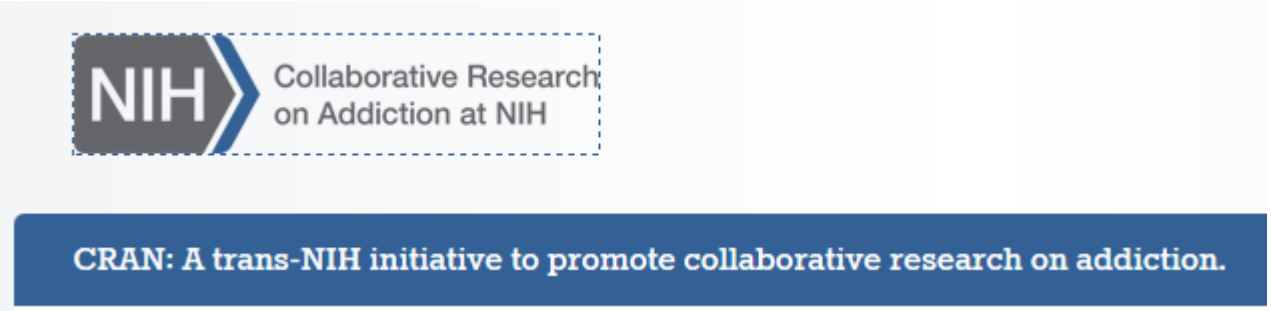
Amanda L. Graham, PhD
Director, Research Development
Schroeder Institute for Tobacco Research & Policy Studies

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

LEGACY | The Schroeder Institute FOR TOBACCO RESEARCH AND POLICY STUDIES

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

Types of Online Networks	Examples
Open social networks	Facebook, Twitter, Google+
Intentionally designed social networks	The Healthy Lifestyle Network, QuitNet, PatientsLikeMe, BecomeAnEX

Centola D. Social media and the science of health behavior. *Circulation*. 2013; 127(21):2135-44. PMID: 23716382.

Cobb NK, Graham AL, Byron MJ, Niaura RS, Abrams DB, et al. Online social networks and smoking cessation: a scientific research agenda. J Med Internet Res. 2011; 13(4):e119. PMID: 22182518

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

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

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

REF: Cobb NK, Graham AL, Bock BC, Papandonatos G, Abrams DB. Initial evaluation of a real-world Internet smoking cessation system. Nicotine Tob Res. 2005. 7(2): 207-16. PMID: 16036277

Online Social Networks & Abstinence

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

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

[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.

REF: Richardson A, Graham AL, Cobb N, Xiao H, Mushro A, Abrams D, Vallone D. Engagement promotes abstinence in a web-based cessation intervention: cohort study. JMIR. 2013. 15(1):e14. PMCID: PMC3636070.

Preventive Medicine 55 (2012) 233–236

Contents lists available at SciVerse ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

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

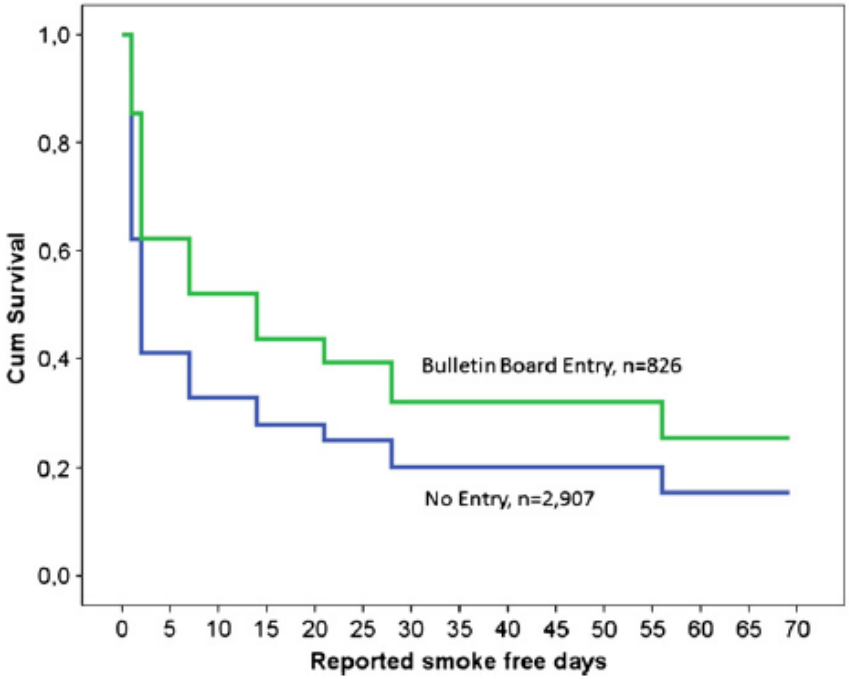


Fig. 2. Maintenance of non-smoking in those who composed their personal bulletin board entry as compared to those who did not contribute (Germany, 2011).

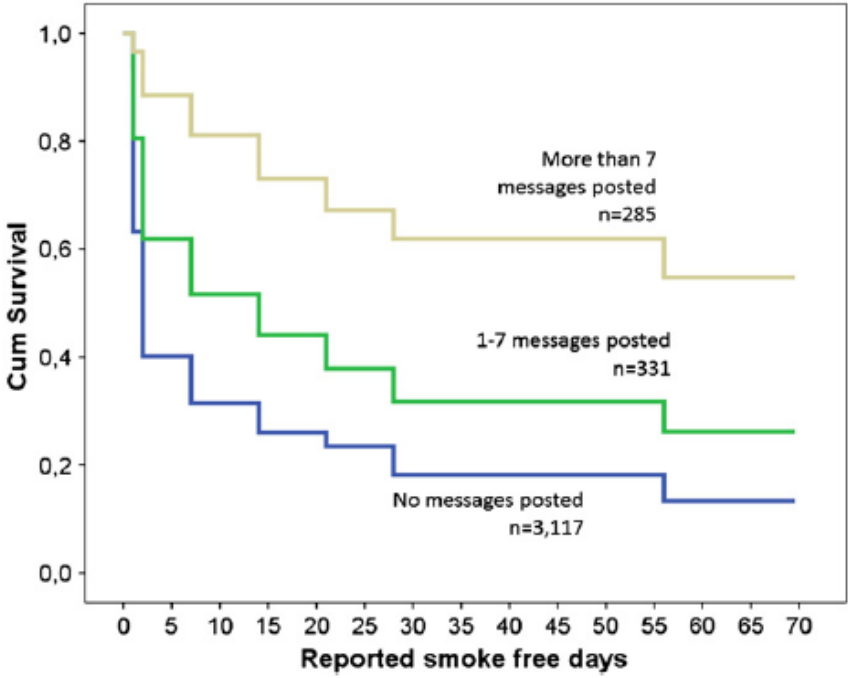


Fig. 4. Maintenance of non-smoking depending on the level of their virtual community activities (Germany, 2011).

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

DOI:10.1093/jncimonographs/lgt025

©The Author 2013. Published by Oxford University Press. All rights reserved.
For Permissions, please e-mail: journals.permissions@oup.com.

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, Kang Zhao, 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 Qiu*, Kang Zhao†, Prasenjit Mitra†, Dinghao Wu†, Cornelia Caragea†, John Yen†, Greta E Greer‡, Kenneth Portier‡
*Department of Computer Science and Engineering
†College of Information Sciences and Technology
The Pennsylvania State University, University Park, PA 16802
‡American Cancer Society, Inc.
250 Williams Street NW, Atlanta, GA 30303

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

Kang Zhao[1], John Yen[2], Greta Greer[3], Baojun Qiu[4], Prasenjit Mitra[2], and Kenneth Portier[3]

[1] Department 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.

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

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

[4] eBay Inc. 2065 Hamilton Ave, San Jose, CA 95125.

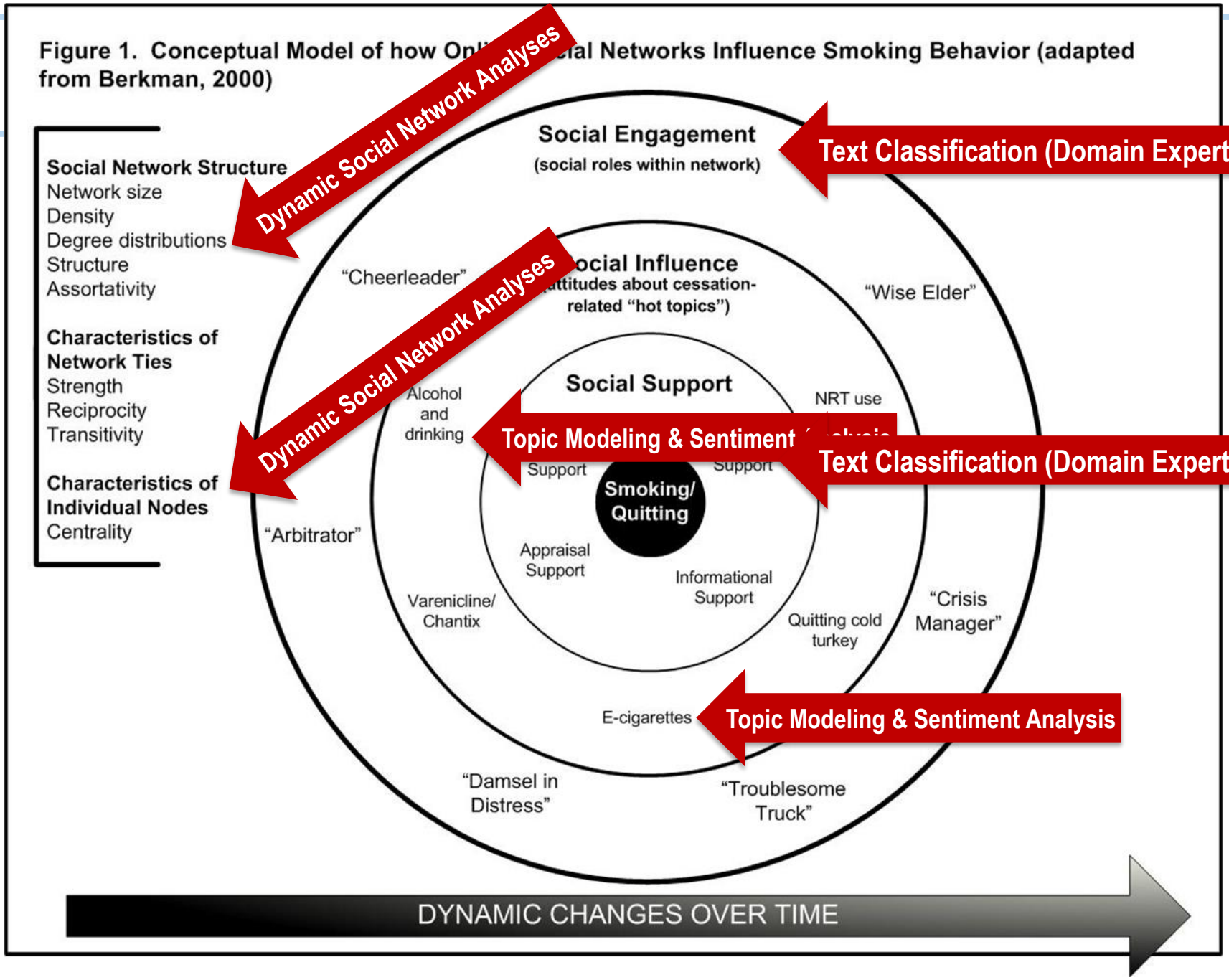


Figure 1. Conceptual Model of how Onl ial Networks Influence Smoking Behavior (adapted from Berkman, 2000)
Social Network Structure
Network size
Density
Degree distributions
Structure
Assortativity
Characteristics of Network Ties
Strength
Reciprocity
Transitivity
Characteristics of Individual Nodes
Centrality
Dynamic Social Network Analyses
Dynamic Social Network Analyses
Social Engagement
(social roles within network)
Text Classification (Domain Experts)
ocial Influence
ttitudes about cessation-related "hot topics")
"Cheerleader"
"Wise Elder"
Social Support
Alcohol and drinking
NRT use
Topic Modeling & Sentiment
Text Classification (Domain Experts)
Support
Support
Smoking/ Quitting
"Arbitrator"
Appraisal Support
Informational Support
Varenicline/ Chantix
Quitting cold turkey
"Crisis Manager"
E-cigarettes
Topic Modeling & Sentiment Analysis
"Damsel in Distress"
"Troublesome Truck"
DYNAMIC CHANGES OVER TIME

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.

Cigarette tracker
Identify triggers
Set quit date
Prepare for quitting
Preventing relapse

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.

Content about Rx
Videos
Adherence

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.

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

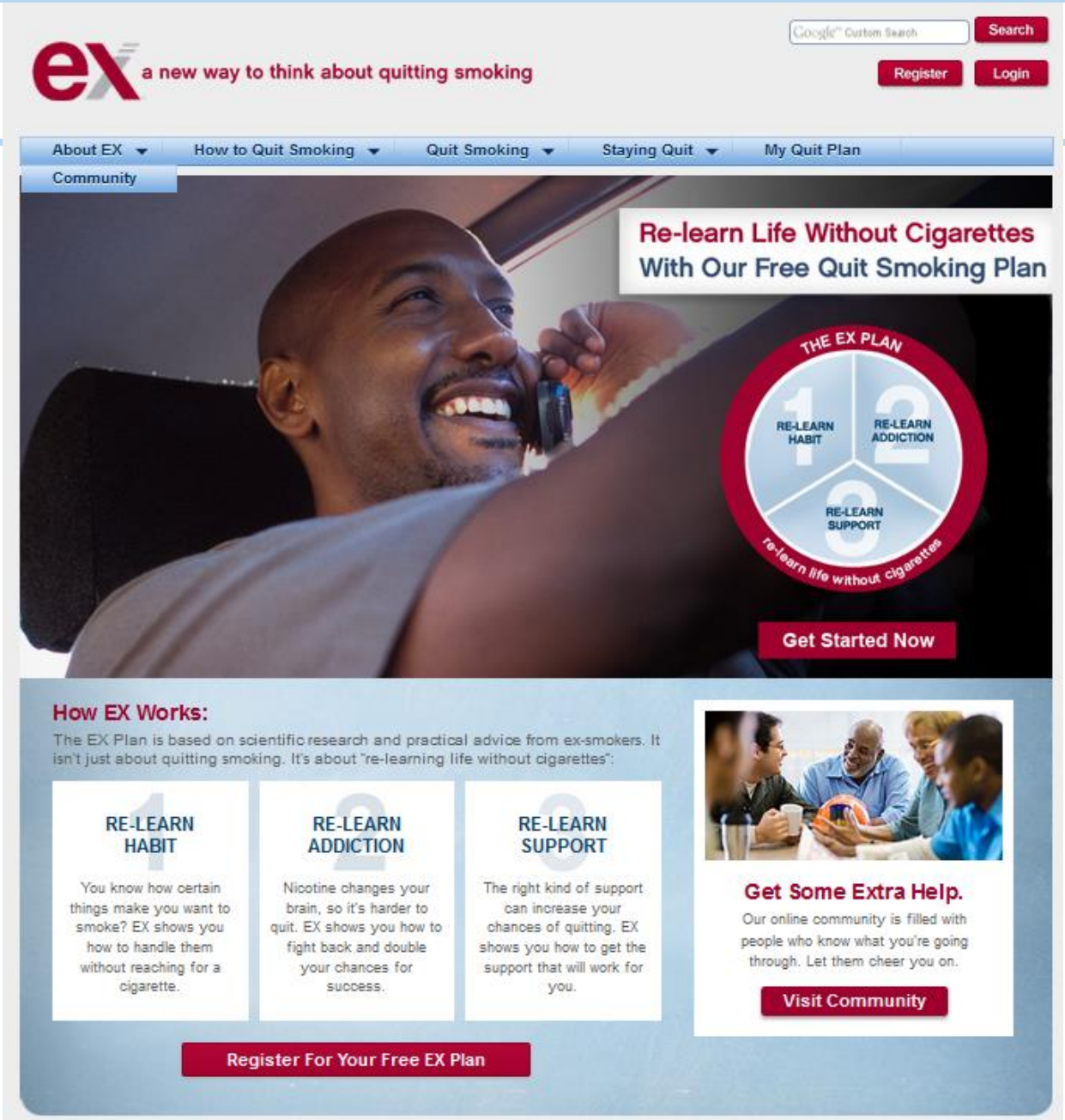
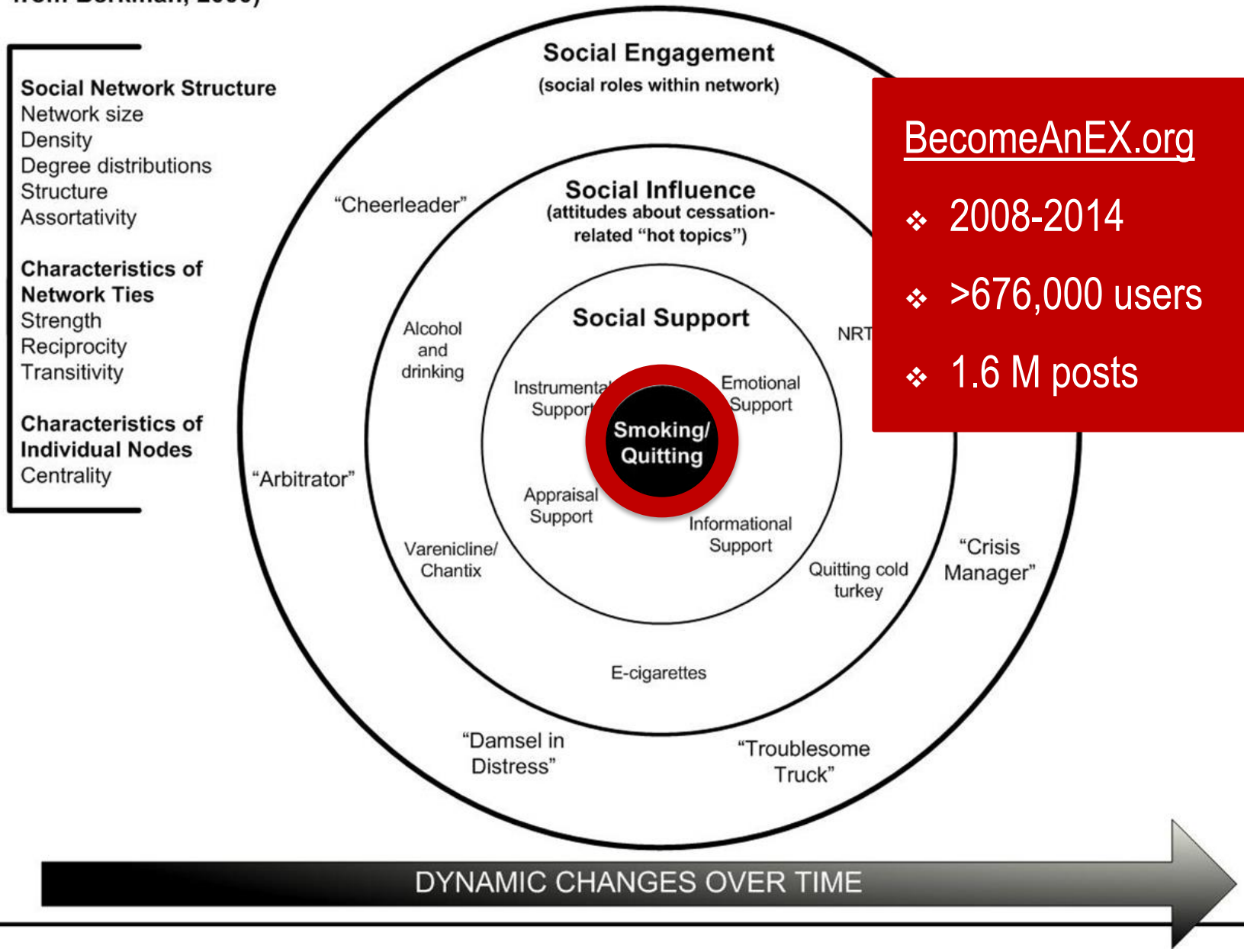


Figure 1. Conceptual Model of how Online Social Networks Influence Smoking Behavior (adapted from Berkman, 2000)



BecomeAnEX.org

- 2008-2014
- >676,000 users
- 1.6 M posts

Original Paper

Engagement Promotes Abstinence in a Web-based Cessation Intervention: Cohort Study

Amanda Richardson[1,2], MS, PhD; Amanda L Graham[3,4], PhD; Nathan Cobb[3,4], MD; Haijun Xiao[1], MS; Aaron Mushro[5], MS, MBA; David Abrams[2,3,4], PhD; Donna Vallone[1,2], MPH, PhD

Abstract

Background: Web-based smoking cessation interventions can have a public heal promoting cessation and can reach large numbers of smokers in a cost-efficient man been realized. It is still unclear how such interventions promote cessation, who benef impact.

Objective: To examine the effectiveness of a highly promoted Web-based smo behavior over time, identify the most effective features, and understand who is most lil and weighted analyses to estimate the impact in the broader pool of registered site u

Methods: A sample of 1033 new adult registrants was recruited from a Web-based automated study management system. Abstinence was assessed by self-report thro with telephone follow-up for nonrespondents) at 1, 3, and 6 months. Software track estimating equations (GEE) were used to examine predictors of website utilization ar unweighted and weighted data.

Results: The 7-day point prevalence abstinence rates at 6 months ranged fro intent-to-treat samples, respectively. Predictors of abstinence in unweighted analyse well as accessing specific interactive or engaging features. In weighted analyses, only Motivation to quit was a key predictor of website utilization, whereas negative increasing visits or accessing engaging features.

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.

- N=1033 BecomeAnEX members
- Cohort study (2011)
- Follow-up 1, 3, 6 months
- Response rates: 69.4% (1mo), 60.3% (3mo), and 53.9% (6mo),

(J Med Internet Res 2013;15(1):e14) doi:10.2196/jmir.2277

Graham *et al. Trials* 2013, **14**:48
http://www.trialsjournal.com/content/14/1/48

TRIALS

STUDY PROTOCOL **Open Access**

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

Amanda L Graham[1,2*], Sarah Cha[1], George D Papandonatos[3], Nathan K Cobb[1,2,4], Aaron Mushro[5], Ye Fang[1], Raymond S Niaura[1,2,4] and David B Abrams[1,2,4]

Abstract

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

Trial registration: ClinicalTrials.gov ID: ISRCTN45127327

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

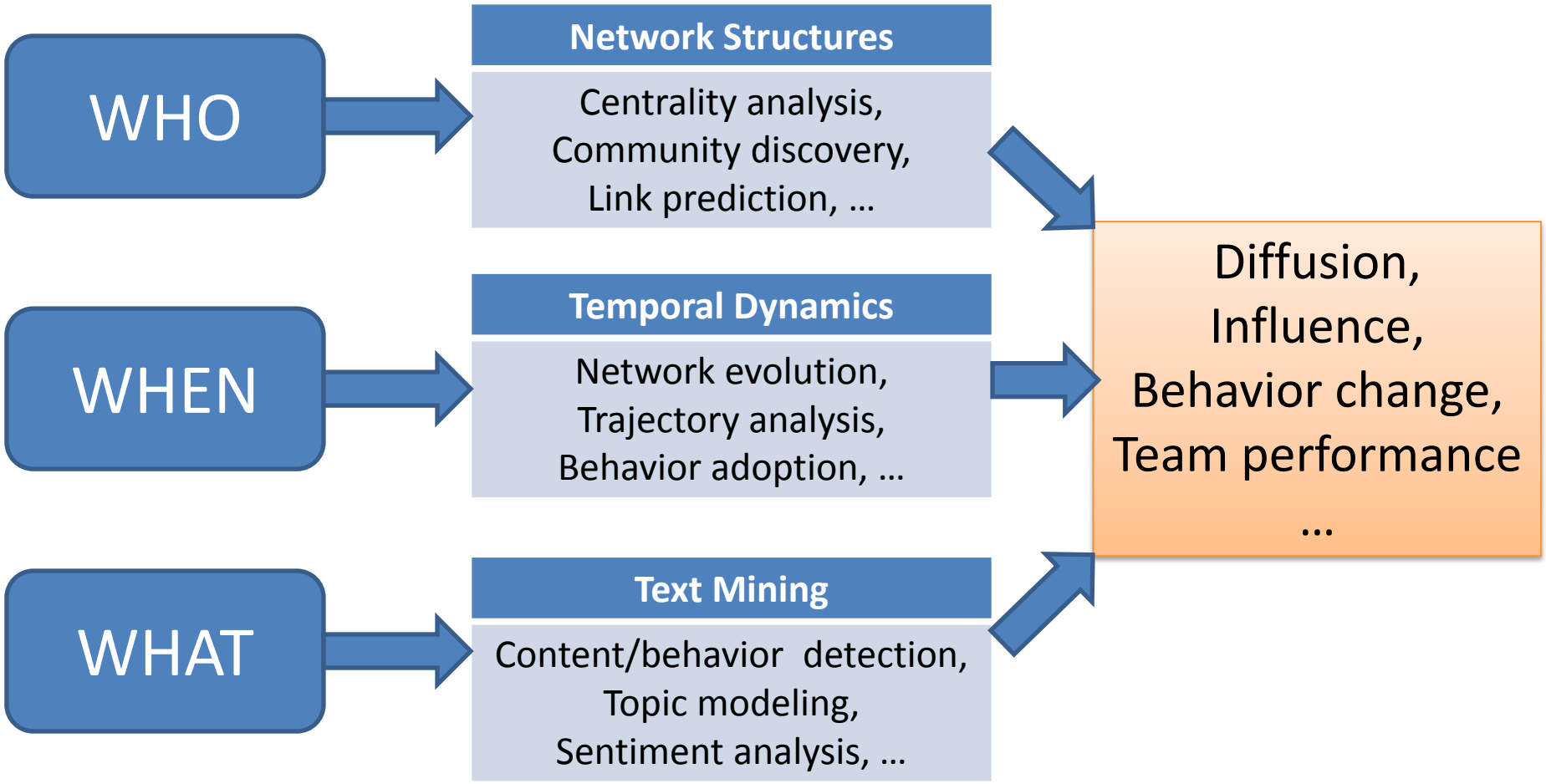
Interdisciplinary Graduate Program in Informatics

The University of Iowa

Social networks and social media

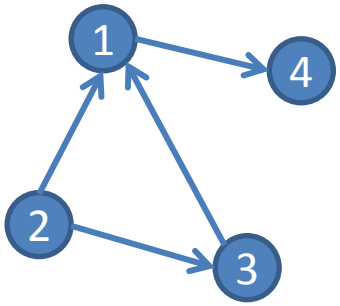
35% of U.S. adults have gone online for medical and health information;
24% also sought information or support from peers who have the same health condition

Leverage the big data from social network/media



Social network 101

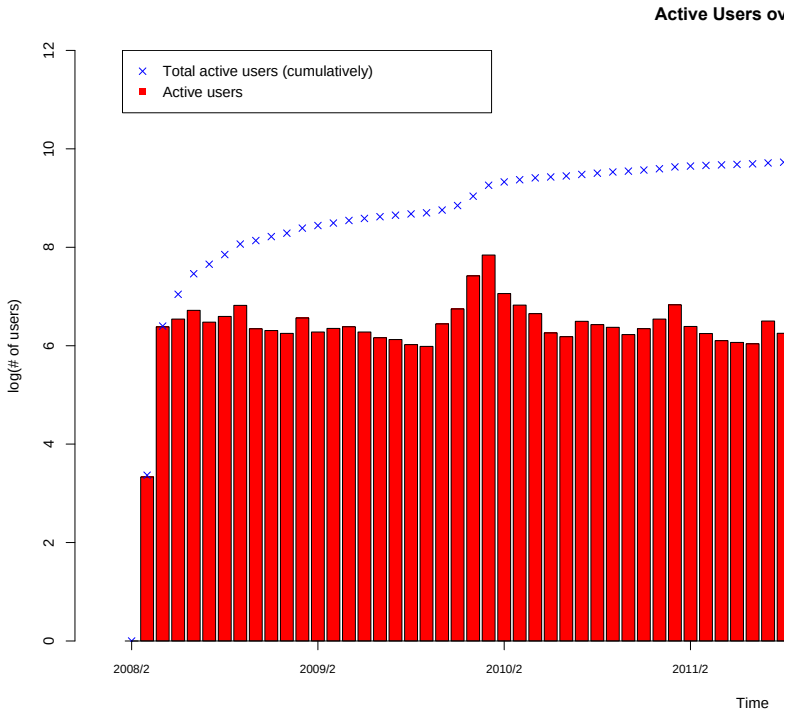
- A social network consists of nodes and edges
  - Nodes represent individuals
  - Edges represent relationships
    - Friendship, kinship, colleague, …
    - Edges can have directions
      - Directed edges: Twitter following, paper citation, …
      - Undirected edges: Facebook friends, collaboration,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

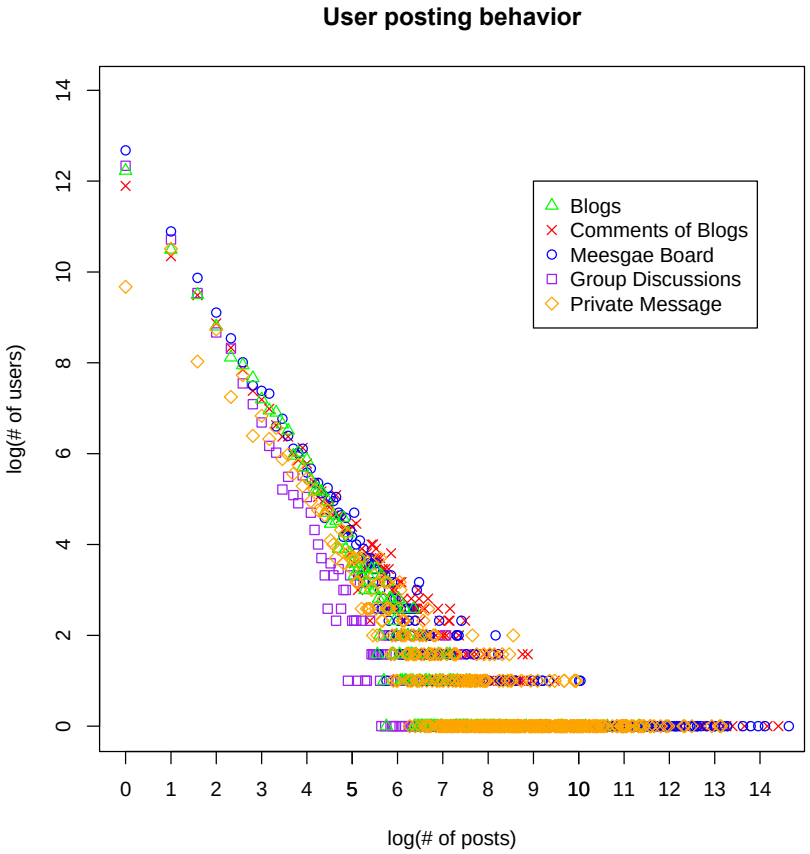


- Degree centrality
  - In undirected networks: total # of neighbors
  - In directed networks:
    - In-degree: # of incoming edges
    - Out-degree: # of outgoing edges

BecomeAnEX Data

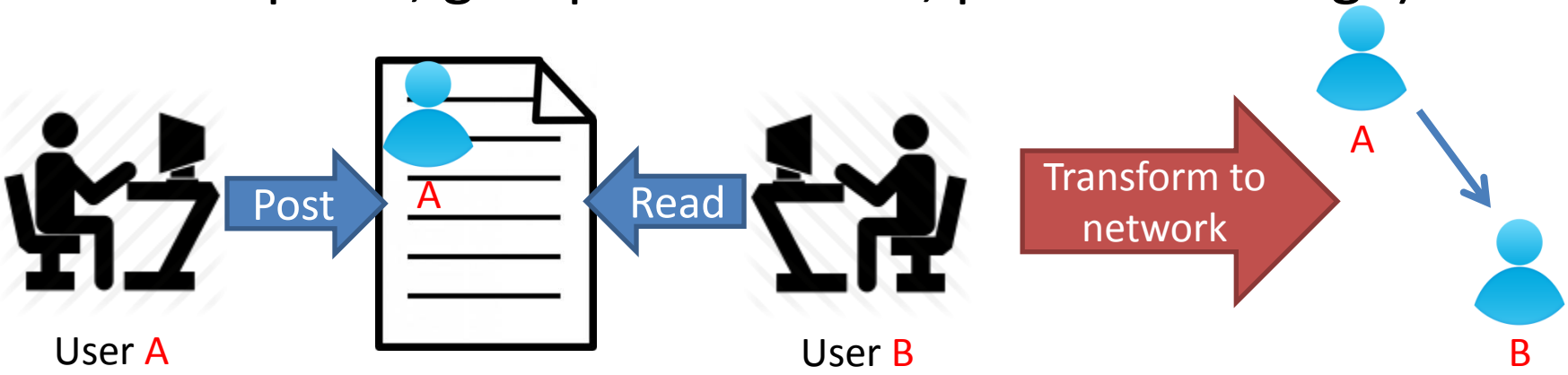
5 years, 676.7k users, 1.5 million posts/messages, 6.2 million page views.



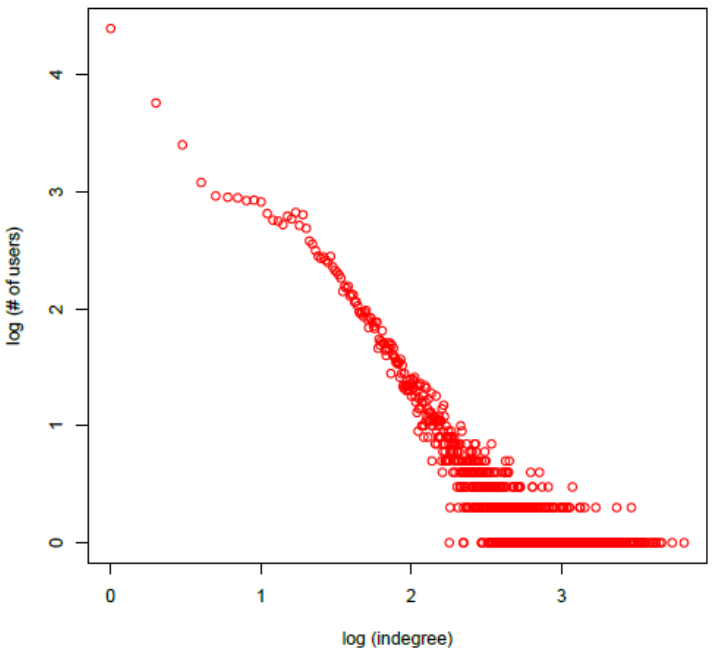


Social networks in BecomeAnEX

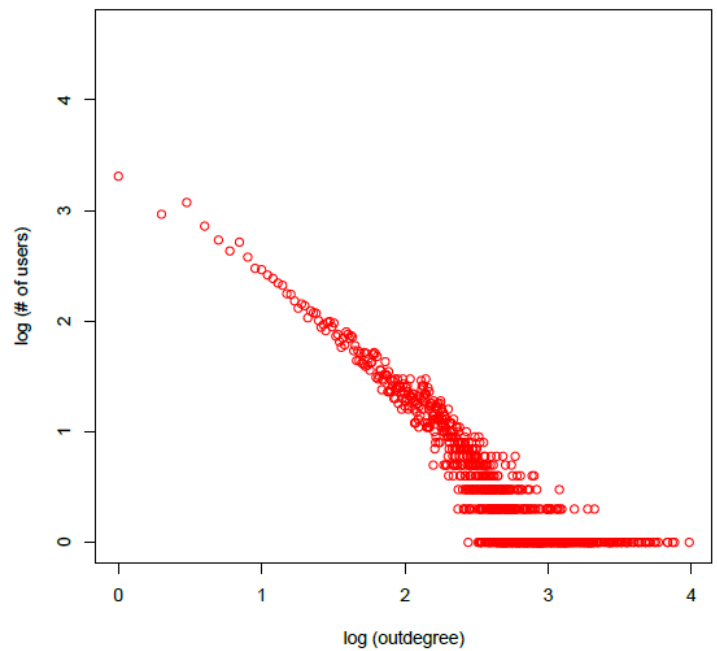
- Nodes:
  - Users of BecomeAnEX
- Edges:
  - Directed
  - Represent the flow of information/support via several communication channels (blog, comments, wall posts, group discussions, private message).



Basic statistics of the network



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

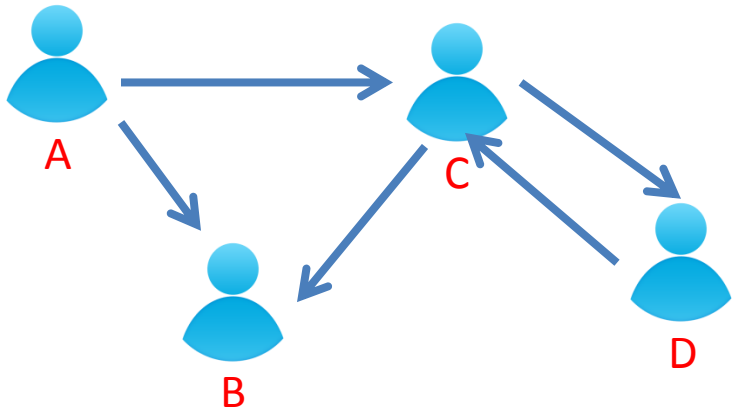


Out-degree: how many other users a user has influenced/supported

Metrics	Values
Num. of nodes with degree >0	58,941
Number of edges	1,466,643
% of reciprocated ties	25.36%
% of nodes in the LSCC	21.43%
Avg. shortest path length in LSCC	2.51

LSCC (the largest strongly connected component) is the largest group of nodes, in which there is a possible path between every pair of nodes

Social network vs behavior change



- 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

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

Similarity among subnetworks

- Structural similarity measured by edge overlap

Subnetwork pairs	Edge overlap
Blog vs Message Board	0.21
Blog vs Group Discussion	0.04
Message Board vs Group Discussion	0.04
Private Message vs Blog	0.02
Private Message vs Message Board	0.01
Private Message vs Group Discussion	0.01

- Similar results if we examine degree correlations.

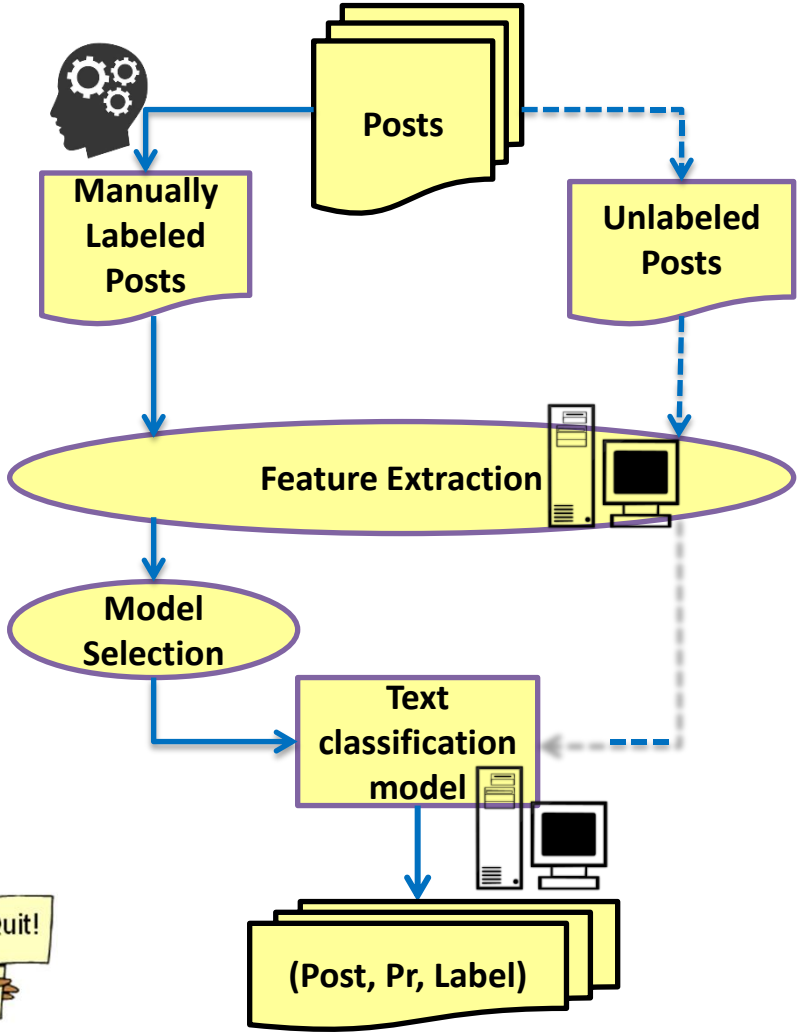
Co-evolution of the subnetworks

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

1st tie	P(1st tie)	P(forming 2nd ties |1st)	Top sequence	P(forming 3rd ties |1st)	Top sequence
Blog	34.6%	28.7%	BL→MB	1.7%	BL→GD→MB
Message Board	42.4%	13.1%	MB→BL	1.0%	MB→BL→GD
Group Discussion	19.4%	11.6%	GD→MB	5.8%	GD→BL→MB
Private Message	3.8%	15.1%	PM→BL	12.7%	PM→BL→MB

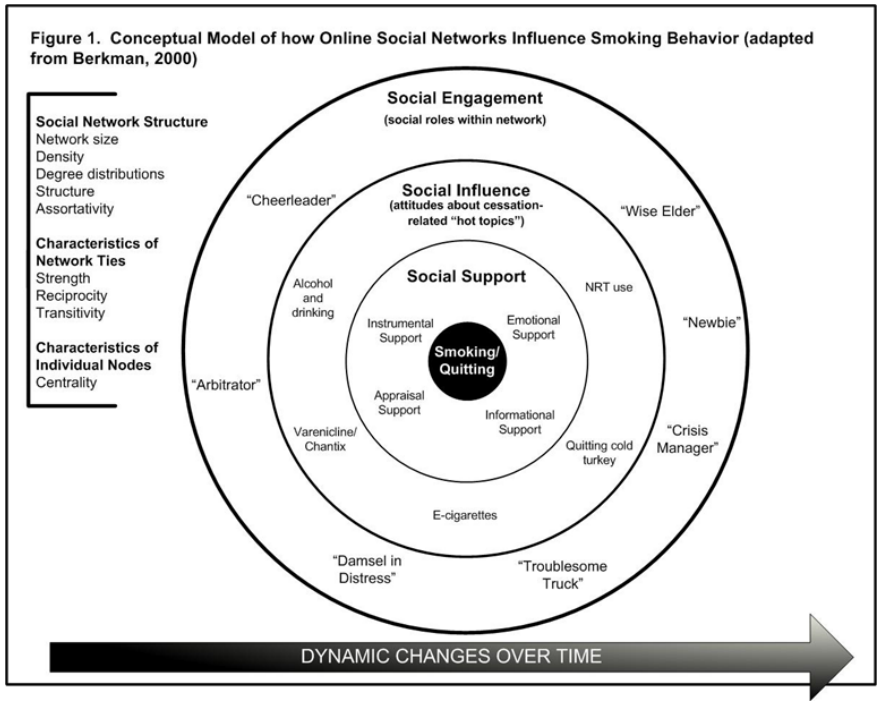
Text mining

- Automated analysis of large-scale text data
  - Does a post contains informational support?
  - Does a post contains 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

LEGACY | The Schroeder Institute FOR TOBACCO RESEARCH AND POLICY STUDIES

References

Qiu, B., Zhao, K., Mitra, P., Wu, D., Caragea, C., Yen, J., … Portier, K. (2011). Get online support, feel better--Sentiment analysis and dynamics in an online cancer survivor community. In Proceedings of the Third IEEE International Conference on Social Computing (SocialCom'11) (pp. 274–281). Boston, MA.

Portier, K., Greer, G. E., Rokach, L., Ofek, N., Wang, Y., Biyani, P., … Yen, J. (2013). Understanding Topics and Sentiment in an Online Cancer Survivor Community. JNCI Monographs, 2013(47), 195–198.

Zhao, K., Yen, J., Greer, G., Qiu, B., Mitra, P., & Portier, K. (2014). Finding influential users of online health communities: A new metric based on sentiment influence. Journal of the American Medical Informatics Association, 21(e2), e212–e218. http://doi.org/10.1136/amiajnl-2013-002282

Zhao, K., Greer, G., Yen, J., Mitra, P., & Portier, K. (2014). Leader identification in an online health community for cancer survivors: a social network-based classification approach. Information Systems and E-Business Management, (forthcoming). http://doi.org/10.1007/s10257-014-0260-5

Wang, X., Zhao, K., & Street, W.N. (2014). Social Support and User Engagement in Online Health Communities. In Proceedings of the International Conference for Smart Health. (pp. 97–110). Beijing, China: Springer. http://doi.org/10.1007/978-3-319-08416-9_10

Wang, X., Zuo, Z., & Zhao, K. (2015). The Evolution and Diffusion of User Roles in Online Health Communities – A Social Support Perspective. In Proceedings of IEEE International Conference on Healthcare Informatics 2015 (ICHI 2015) (forthcoming), Dallas, TX.