SAND2011-2407C

Extending Opinion Dynamics to Model Public Health Problems and the Evaluation of Policy Interventions

Authors:

Thomas Moore, Patrick Finley, John M. Linebarger, Alexander Outkin, Stephen Verzi, Nancy Brodsky, Daniel Cannon, Robert Glass

Abstract

The public health community is recognizing the importance of social network dynamics in analyzing lifestyle diseases correlated with behaviors including tobacco and alcohol use, substance abuse, and obesity. These behaviors are driven in part by opinions that individuals hold regarding products, behaviors, and lifestyles. The opinions and behaviors of individuals are influenced by their personal social networks, as well as exogenous components, such as advertisements.

We extend the basic opinion dynamics model to include two processes important for analysis of lifestyle diseases. The first is an antagonistic reaction that drives individuals further apart in opinion space; the second is the addition of hysteresis representing the constraint addiction places on an individual's behaviors.

We apply this extended model to consider tobacco use within a community and various approaches to influence its prevalence, including advertisements and health-related educational campaigns. We examine the roles of advertising strength, the strategic importance of tolerance, and how hysteresis in the behavioral function influences tobacco usage within a community.

Finally, we show how spatially and temporally local results can act as inputs to a population-wide, long term system dynamics model. This allows for the examination of the impact of interventions on future mortality.

Introduction

Lifestyle diseases are diseases which are strongly correlated with individual behavioral components and which can develop or progress due to lifestyle choices of individuals. These diseases, including some types of heart disease, cancers, and many metabolic disorders such as diabetes often correlate with behavioral components such as diet and physical activity, smoking, and alcohol and substance abuse.[1-3] Studies have demonstrated social network based clustering effects for lifestyle diseases which are similar to those shown for communicable diseases.[4-6] Analysis of social network mediated interactions has proven fundamental to the understanding of contagious disease epidemics, such as influenza.[7] Although the lifestyle diseases themselves are often not considered communicable diseases, similar propagation of behaviors through social networks may be a causal factor in patterns of lifestyle diseases in the population. [8]

As individuals interact with others in their social networks, they exchange beliefs, ideas, and opinions in both direct and indirect ways. As an example, simple discussion of ideas and opinions between members often leads to some individuals convincing others to modify their opinions about the concepts or beliefs discussed, while extended social interaction can result in each individual gradually modifying his or her opinion toward a more consensual view in search of "common ground." This phenomenon may be seen as an application of what social psychologists have identified as structural balance theory, which states that a positive affective relationship between two individuals will tend to lead them towards similarity in their affective relationships to a third individual or concept.[9] In addition to these relationship-mediated means of opinion and belief exchange between individuals in social networks, media sources can influence the opinions held by members of a community via elements exogenous to the immediate social networks, via mechanisms including television, billboards, and radio broadcasts.

Direct and indirect exchange of opinions and ideas within social networks may result in changes in individuals' behaviors. To the extent that an individual's actions are influenced by their opinions, it can be seen that changes in opinions may result in changes in behaviors. If opinions can be seen as propagating through networks, and opinions influence behaviors, then one of the most direct observable results would be a tendency of the resulting behaviors to cluster in social networks, forming smaller sub-networks of individuals with similar opinions.

Opinion dynamics modeling is a recently developed family of approaches for the analysis of social influences on individual opinions, and the emergence of resulting community-scale patterns. These models have been developed by the statistical physics community and are grounded in Ising models of particle spin alignment in lattices.[10] These models encompass significant variation in approaches: binary, discrete, or continuous opinion values; unstructured, linear, lattice, or complex network topologies; and random or averaging interactions. However, all opinion dynamic formulations share common theoretical roots, and all generate clusters of individuals sharing similar opinions based on local rules governing individual interactions. In these models, a set of individuals are used to populate a community, and are seeded with initial opinion values. Each individual updates her opinion based on interactions with her neighbor(s). These interactions are potentially governed by network topologies, randomness, and similarity in individual opinions.

Opinion Dynamics Model

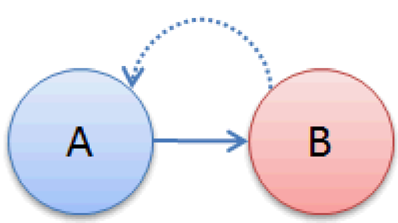
Our model extends a widely used model introduced by Deffuant et al.[11] This approach, frequently referred to as the Deffuant-Weisbuch (DW) model, was initially constructed using randomized interactions among individuals in a well-mixed population. Individuals are assigned a random opinion, taken as a value on the continuous interval [0, 1] drawn from a uniform distribution, and a tolerance threshold, ε. At each time step, two individuals are selected at random from the population. If the difference in opinions between the individuals is within the tolerance threshold (that is, the opinions are within ε of each other), the individuals update their opinions according to the equation:

$$x_i(t+1) = x_i(t) + \mu[x_j(t) - x_i(t)]$$

$$x_j(t+1) = x_j(t) + \mu[x_j(t) - x_j(t)]$$

Here, $x_i(t)$ and $x_j(t)$ represent the current opinion values of the first and second person, respectively; $x_i(t+1)$ and $x_j(t+1)$ represent the values at the next time step. The plasticity factor μ represents the extent to which individuals are swayed by their neighbor's opinions represents the plasticity of the individual opinions and determines the rate of convergence.

We apply the DW model to directed social networks. Directed social networks can represent types of relationships often characterized as nominations, for example, as gathered in a survey asking individuals to name their closest friends. Directed social networks are depicted graphically with an arrowhead on one end of an edge linking two individual nodes. Directed edges are often named "-out-edges" or "-in-edges" relative to a node. If an edge's arrowhead points away from a node, then the edge is an -out-edge. Conversely, the arrowhead of an -in-edge points to the node in question. By convention, the direction of the arrow represents the direction of nomination; a node's influence on opinion flows in the direction opposite to the arrowhead. This means that if *A* nominates *B* as a friend, but *B* doesn't nominate *A*, the network would show a single edge between nodes A and B with the arrowhead pointing to B. Opinion flow would be from B to A, since we expect *A* to be influenced by *B*'s opinion, but not vice versa.



Figure??: A names B as a friend, so a sociogram depiction shows an arrow pointing from A to B (solid line). The directed flow of opinion moves in the opposite direction (dashed arrow).

We interpret the dynamics of the model to represent overall social influences from all nominated individuals, rather than discrete pair-wise interactions. That is, the model is considering the continuous interactions between friends, rather than the discrete exchanges that would occur in a deliberation on a particular subject. In the case of a node with multiple out-edges (for instance, an individual who has named more than one person as a friend), we average over the opinions of the connected nodes. Our equation becomes:

$$x_i(t+1) = x_i(t) + \frac{1}{|T_i|}\sum_{j\in T_i} \mu_{ij}(x_j(t) - x_i(t))$$

This averaging effect is similar to the one proposed by Hegselmann and Krause.[12]

Here, $|T_i|$ is the cardinality of T_i, and T_i is the set of all out-degree neighbors of x_i whose opinions fall within the tolerance threshold, determined by evaluating the absolute value of the difference in opinions against the tolerance value:

$$|x_i(t) - x_j(t)| \leq \varepsilon_i$$

The model can be viewed as a social network of individuals seeking to gain consensus with their neighbors. At each time step, each node of the social network graph adjusts its opinion value to a value closer to the mean of its neighboring nodes. When this process is applied across all nodes of a network, opinions of nodes in certain portions of the graph will tend coalesce to common mean values, with the number and average size of the clusters primarily determined by the constraining tolerance variable ε.[13] The portions of the graph whose nodes display similar opinion values define opinion clusters. Over repeated time steps, the opinion dynamics model causes the social network to shift from isolated nodes with randomly distributed opinions to clusters of neighboring nodes sharing a common opinion.

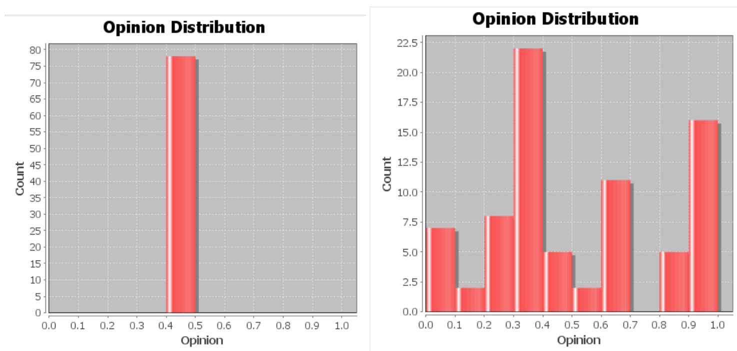


Figure ?? Histograms showing opinion distributions for a 75-node scale-free network with tolerance=0.5 (Left) and tolerance=0.2 (Right)

Network Topologies

Social network topologies control which nodes are direct neighbors to a given node. While survey-based social networks are useful for determining social relationships within a community, such surveys must be well constructed and the resulting responses carefully analyzed. Random networks constructed to resemble those obtained from surveys are a useful alternative which allows many different social network structures to be investigated efficiently

Random networks form the basis for our simulations using opinion dynamics to model public health issues. Scale-free networks are often created using the method of preferential attachment. Preferential attachment network construction generates topologies that exhibit a power law distribution of node degree.[14] This network topology has been repeatedly discovered in a wide variety of phenomena, including computer networks and websites, protein interactions in cellular physiology, and social networks representing friendships, advice-seeking, and sexual relations.[15] Preferential attachment explains some, but not all, topology in friendship networks.[16] We modify a scale-free network to include a proportion of edges between randomly selected nodes, resulting in a network that is predominantly constructed using the Barabasi-Albert model of scale-free network construction, with a smaller proportion of edges determined by an Erdos-Renyi random process.

Antagonism

A variety of interactions can be modeled with DW opinion dynamics models. The original definition of DW opinion dynamics specifies two types of potential interactions between individuals: positive interactions, in which the individuals' opinions move closer to one another, and neutral interactions, in which the opinions are considered too far apart, and so no adjustment takes place. Although these two possibilities capture a wide range of potential interactions, some researchers have recently added a third possibility: a negative interaction that drives the opinions of the individuals further apart; the potential for this antagonistic response is attributed to the "ego-involvement" of the individual agents, according to an interpretation of Social Judgment Theory.[17]

If an interaction occurs between individuals whose opinions differ by an amount greater than the antagonism threshold value, the resulting change in opinions is identical in magnitude to the original equation, but opposite in sign:

$$x_i(t+1) = x_1(t) - \frac{1}{|A_i|}\sum_{j\in A_i} \mu_{ij}(x_i(t) - x_j(t))$$

Here, A_i is the set of all out-degree neighbors of x_i whose opinions fall within the bounds of antagonism.

Addition of antagonistic responses to simple DW dynamics enables us to simulate a more complete range of opinion-dynamics interactions between agents:

1. Consensus with entities adopting new opinions closer to their neighbors whose opinions are already similar
2. Indifference with entities not affected by opinions of their neighbors where opinion differences exceed the tolerance threshold epsilon
3. Polarization with entities adopting widely divergent opinions when opinion difference is greater than the antagonism threshold.

Analyzing Smoking Using Opinion Dynamics

We consider the case of cigarette smoking in a community as an illustration of an application of these ideas to the analysis of policies. In addition to smoking being the leading cause of preventable deaths in the United States, causing 18.1% of total deaths in 2000[18], multiple researchers have demonstrated strong correlations between tobacco use and social network relationships.[6,19,20]

Youth experimentation with smoking is primarily catalyzed by psychosocial motivations, especially aspirational components which include rebellion and an assertion of independence and adulthood.[21] The tobacco industry capitalizes on these aspirational components by targeting brands to specific socio-economic segments and designing marketing campaigns that create associations between these aspirational components and tobacco products.[21-23]

We interpret the opinion value of an individual to represent that individual's opinion about smoking in this opinion dynamics investigation of tobacco use. Ideas such as "Smoking helps people control their weight" and "Smoking is cool" could contribute to a favorable opinion about smoking. Alternatively, ideas including "Smoking causes lung cancer" and "Second-hand smoke is dangerous" could contribute to a non-favorable opinion about smoking. We interpret the opinion value for a given agent to be an aggregate value representing the agent's belief in all such ideas. Using a continuous range of opinion over [0, 1], we interpret an opinion value of 0 to be extremely anti-smoking, an opinion of 1 to be very favorably disposed toward smoking, and opinions on the range [0.45, 0.55] to be essentially neutral on the topic.

Opinion-Behavior Mapping

Opinions are of interest in this investigation because they are assumed to affect behavior. For purposes of simplicity, our model proposes a simple step function, with the value of the behavior being either *true* or *false*. We set an initiation threshold for opinion; when an agent's opinion exceeds the threshold value, the agent initiates the behavior. The initiation threshold can be interpreted as a subjectively assigned measure of utility of tobacco use to the individual. If the perceived utility cost of a behavior is high, the individual needs a higher opinion about the behavior than they would if the cost was relatively low. Cost should be interpreted as not only monetary cost, but also convenience. Initiation thresholds for smoking could be raised by increasing the purchase price for a pack of cigarettes, but also through indoor smoking restrictions or age-based point-of-sale restrictions, either of which make acquiring or smoking cigarettes more difficult.

We apply hysteresis in the function that maps opinion to behavior when the behavior of interest has a physiologically or psychologically addictive component. This formalizes the notion that addiction compels an individual to maintain the behavior even when her opinion falls below that which would cause initiation. We can allow for various degrees of addictiveness of products and addiction of individuals by setting a cessation threshold to some value less than the initiation threshold. In the case of cigarette smoking, the cessation threshold can be increased, thus lowering the effects of addition, through the use of support groups and nicotine replacement therapy.

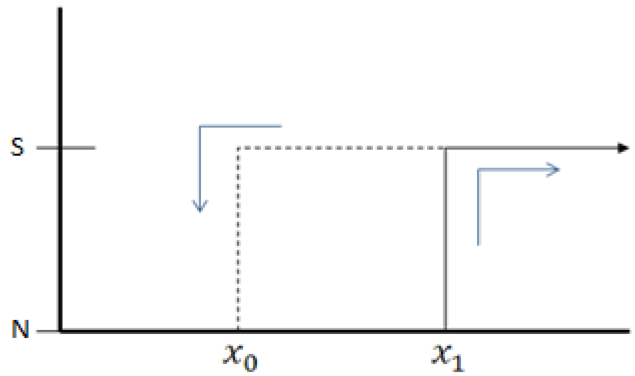


Figure ???. Graphs illustrating addiction hysteresis. In this graph, x_1 represents the initiation threshold, x_0 represents the cessation threshold, S represents smoking, and N represents non-smoking. The hysteresis effect is in place as an individual's opinion moves from x_1 to x_0, creating an intermediate region of length $\Delta x = x_1 - x_0$ in which a smoker will continue to smoke despite his or her opinion falling below the initiation threshold.

Scenarios

We apply our model to the analysis of three different scenarios to illustrate the utility of modeling for public health policy evaluation. First we examine how advertising and educational campaigns influence opinions and resulting behaviors in social networks. Next we examine information campaigns which add efforts to modify individual tolerances at strategic locations in the network. Lastly we examine the effects of policies which could shift threshold values for initiation and cessation.

Using Advertising and Education to Influence Opinion

We model the effects of this information flow by allowing the model to determine population clusters resulting from different levels of initial opinions and tolerance thresholds. Agents external to the social network representing, for example, industry and health advocacy groups, attempt to modify the behavior of individuals through the use of advertising and educational campaigns. We model information flows from these external sources as media nodes which inject new opinion values to selected individuals within the network. We have adopted a terminology convention to differentiate efforts by the tobacco industry from those of public health groups. We refer to industry efforts to promote the smoking as "Advertising". Conversely, public health messaging campaigns to counter the behavior or encourage healthier alternatives are denoted as "Education".

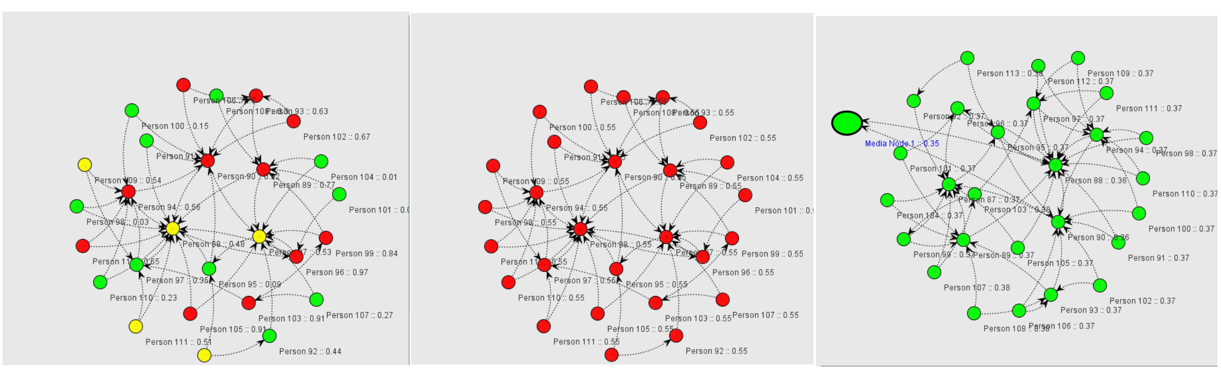
We consider an advertising or educational campaign to be a specialized media node having only in-edges. This indicates that information flows from the specialized media node to other connected nodes. That is, people may be influenced by an educational poster at a bus station, but they cannot, in turn, directly influence the opinion of that poster.

Advertising and public-service education seeks to communicate with the most influential members of a social network, in hopes that the message will then propagate from the influential individuals to others. An advertising or educational node can be configured to connect with influential nodes in the social network by targeting nodes with specific network properties. For example, social network members who regularly communicate with many others in the network are represented by network nodes having greater degree (number of in-edges). By targeting these individuals whose network node importance measures are high, the model encapsulates accepted marketing and public-relations concepts. To in effect behavioral change across the social network, our model allows us to examine the effectiveness of different network-node importance metrics such as degree centrality, and betweenness. Advertising and educational nodes attempt to influence the network as a whole by injecting an opinion value into these important connected nodes using the same modified DW opinion dynamics mechanism introduced above.

An advertising campaign can attempt to raise opinions about smoking through positive associations. We can model such a campaign as an attempt to influence the network strongly by projecting an opinion value close to 1 to important nodes. Similarly, an educational campaign can attempt to dramatically lower opinions by espousing an opinion value close to 0. These extreme values, however, can fall outside the range of tolerance for the individual nodes to which they are attached, either failing to influence or, as a result of antagonism, pushing the individual and the network in the opposite direction.

We find that the ability for a node to influence the network via opinion propagation is primarily determined by the individual's PageRank, a centrality ranking algorithm closely related to Eigenvector ranking. PageRank emphasizes importance as determined by random walks through the graph. The importance of a node using the PageRank method is determined not only by the number of nodes pointing to it, but also the relative importance of those nodes.[24]

[SA OF PAGE RANK CAN GO HERE]



Figure??? Showing initial social network, steady state without educational node, steady state with educational node. N=17, tolerance=0.3, media node opinion=0.35

xx

The ability of a single campaign to influence the network is constrained by the tolerance values of the individuals in the network. A network composed of individuals with a low tolerance to opinions of their neighbors' results in many opinion clusters with few individuals in each cluster. Social networks composed of individuals with high tolerance thresholds typically coalesce to one to two dominant opinions. This implies that advertising campaigns conducted on a network with low tolerance can change opinions in these isolated opinion clusters, but a higher tolerance network is required for injected opinion to propagate throughout the network.

A campaign attempting to bring network consensus can force a large part of the network to a moderate opinion value (e.g., [0.40, 0.60]), but has more difficulty bringing a shift to a more extreme consensus. The opinion promulgated by advertising or educational campaigns must be within the tolerance threshold of the targeted individual for the message to effectively shift opinion. Messages that are outside of an individual's tolerance are interpreted to be extreme and are ignored or serve to drive that individual's opinion in a direction opposite of that intended by the campaign. A moderate message is more likely to be within the tolerance threshold of more members of the social network, and thus can be quite effective in shifting opinion to central values. It's also possible for moderate-valued campaigns to decrease extreme opinions from their own side; a campaign promoting a moderately favorable opinion about smoking with an opinion value of 0.60 may end up dragging down network clusters that would otherwise converge to a higher opinion value. The converse possibility holds for campaigns promoting a non-favorable opinion. Thus to shift opinion to extreme values, the injected message must be more extreme than the desired final opinion value. Additionally, extreme messages are more likely to be outside the tolerance of individuals holding moderate or opposite opinions, thus fewer nodes are available to be influenced with a truly extreme campaign.

Opinion toward a lifestyle or behavior can change considerably without the outwardly-directed behavior being affected. The opinion of an individual must exceed the initiation threshold for the characteristic behavior to begin and must fall below the cessation threshold for the behavior to cease. Unless the campaigns shift individuals' opinions across one of these thresholds, behavior will not be initiated or stopped. A campaign can therefore be effective in bringing about an opinion shift, but be ineffective in bringing about a significant change in the behavioral regime. In our model, this means that an individual may become favorably inclined toward smoking but be unwilling to bear the financial and convenience costs to adopt the behavior, or conversely they might develop a non-favorable opinion about smoking, but not sufficiently so to overcome their addiction.

Compound advertising or educational campaigns consisting of multiple messages working in concert can increase effectiveness over that of either message alone. A compound strategy employs multiple campaigns. The initial campaign pushes a moderate opinion which is within the tolerance of individuals holding anti-tobacco opinion. This initial campaign serves to shift the opinion of these anti-tobacco individuals to a more moderate position. The follow-on campaign then applies a more strongly pro-tobacco message. non-favorablto then move the already biased network to the desired value. This complementary effect can be used to generate a widely held consensus at a value well above or below the initial mean opinion.

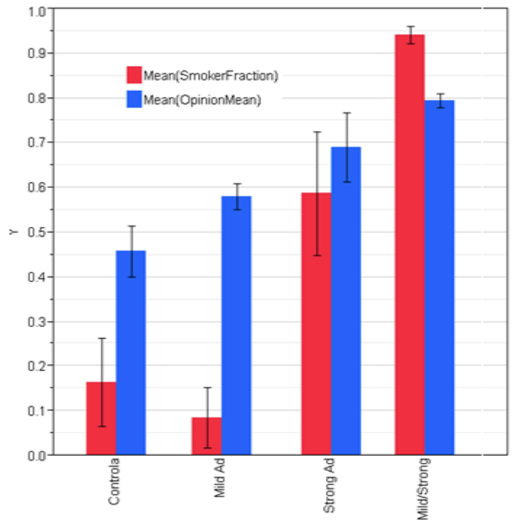


Figure ??. Results of complimentary advertising analysis. Bars represent mean final values for model run over 204,000 different generalized social networks of 250 nodes. Red bars indicate fraction of population who smoke. Blue bars indicate mean opinion on tobacco for population (0.0 = Unfavorable, 1.0 = Favorable). Error bars indicate 95% confidence interval of the mean. *Control* indicates model results without injection of opinion to most important nodes. *Mild Ad* corresponds to injection value of 0.65. Strong Ad indicates injection value of 0.85. *Mild/Strong* indicates half of the most important nodes receiving opinions of 0.65 and half receiving opinions of 0.85. Note that *Mild/Strong* is most effective at increasing opinion on tobacco and portion of the population who smoke. Additionally, the *Mild/Strong* case generated the most predictable result as indicated by the narrow error bars.

We analyzed the ability for advertising nodes to influence a scale-free network of 250 nodes (Figure ??). Advertising nodes were connected to the top ten nodes determined using the PageRank method. The mild advertisement opinion was set to 0.65, and the strong advertisement was set to 0.85. The control results indicate network behavior in the absence of advertisements. A mild ad acting alone was able to raise the average opinion of the network from approximately 0.46 to approximately 0.58. However, a side effect of the mild ad is to decrease the opinions of individuals below the initiation threshold. This results in the unintended side effect of decreasing the smoking fraction from approximately 16% to approximately 8%.

A strong ad acting alone was able to raise the average opinion significantly higher, albeit with an increase in variability. The average opinion increased from the baseline of approximately 0.46 to approximately 0.69, while the smoker fraction increased from approximately 16% to approximately 58%. The strong ad was thus significantly more effective than the mild ad, both in changing opinion and in changing behavior.

The strongest observed effect comes from combining the two advertising strategies. With both the mild and the strong ads connected, mean opinion was raised to approximately 0.79, while the average smoker fraction increased to approximately 94%.

Using Advertising and Education to Affect Tolerance

Tolerance in opinion dynamics is interpreted to indicate the inclination of an individual to adjust their opinion toward someone with a differing opinion. Tolerance is sometimes termed "lack of certainty" about one's own opinion. Low tolerance values thus effectively limit the breadth of opinions individuals are willing to incorporate into their own. An advertising or educational campaign can affect tolerance if it is designed to adjust an individual's willingness to listen rather than affecting their opinion relative to a product or behavior directly. For example, a claim that expert scientific opinion remains divided on a subject (for example, the effects of environmental tobacco smoke) could lead to an increased tolerance among some individuals, producing a willingness to give more credence to opposing opinions. A tolerance-based campaign might conversely bring about a decrease in opinion by raising questions about bias in the presentation of evidence.

Our research indicates that the ability of an advertising or educational campaign to affect the network is grounded in the tolerance values of the nodes with the highest betweenness centrality. The betweenness of a node is proportional to the number of shortest paths on which it lies, with a greater number of shortest paths running through a node contributing to a higher betweenness rank.

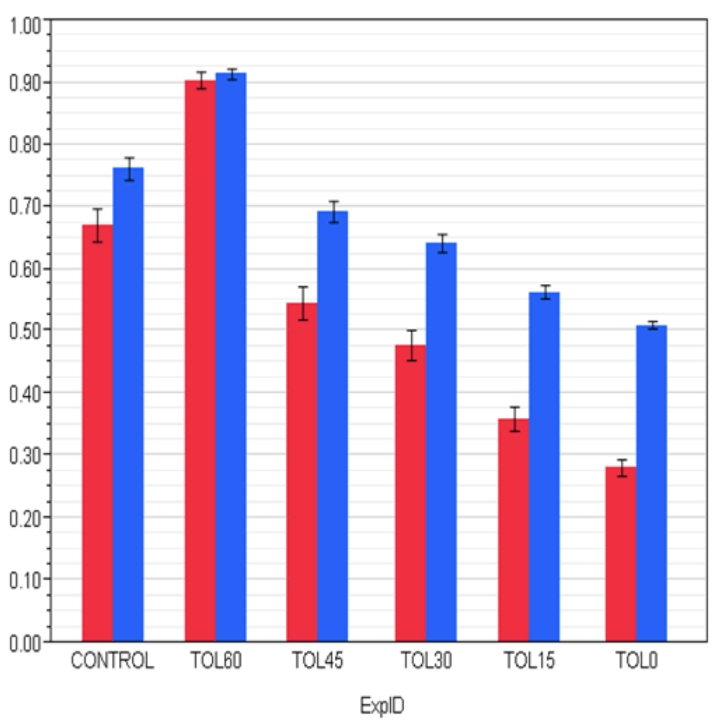


Figure ??. Results of tolerance based advertising analysis. Bars represent mean final values for opinion dynamics model run over 204,000 different generalized social networks of 250 nodes. Red bars indicate fraction of population who smoke. Blue bars indicate mean opinion on tobacco for population (0.0 = Unfavorable, 1.0 = Favorable). Error bars indicate 95% confidence interval of the mean. Control indicates model results without injection of opinion to most important nodes. Other categories correspond to the values of tolerance injected into the 10 most important nodes from 0.6 (TOL60) to 0.0 (TOL0) as ranked by betweenness centrality.

We analyzed the ability of an advertising node to influence the opinions and behaviors in a scale-free network of 250 people (Figure ??). The network was initialized with a uniform distribution of opinions on the range [0, 1] and the advertising node was propagating an opinion of 1.0 (Very favorable to tobacco). Baseline tolerance for nodes was set to 0.50. The advertising node was connected to the four nodes with the highest PageRank values. Tolerance values were varied for the six nodes with the highest betweenness rankings.

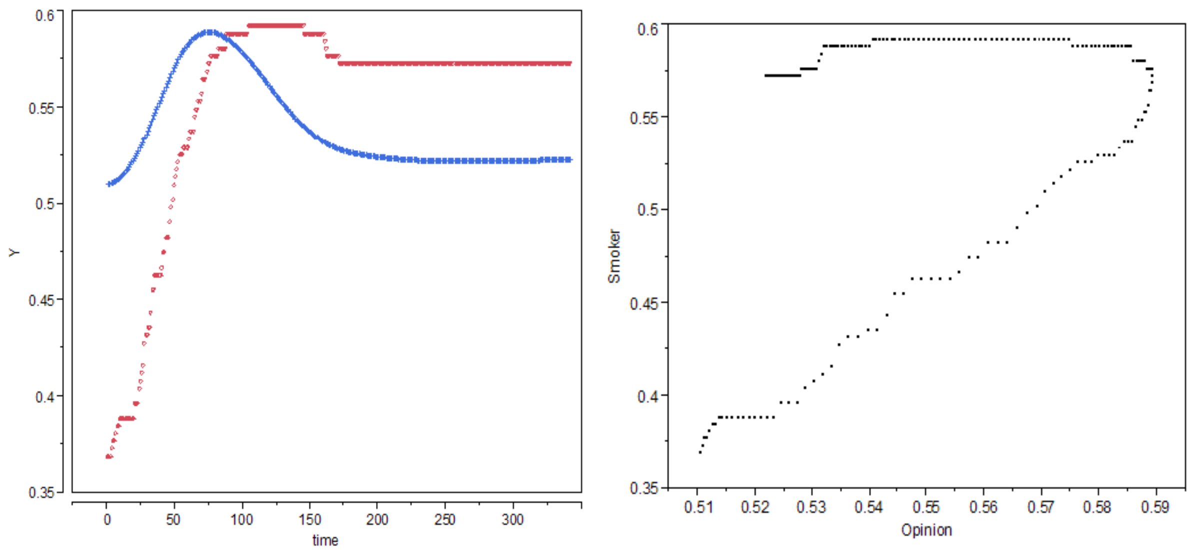
Our results indicate that adjusting the tolerance threshold for just those six nodes (2.4% of the network) can have a dramatic effect on the ability of an exogenous media campaign to shape the opinions and behaviors in the network. Raising the tolerance value of those six nodes to 0.6 resulted in an increase in the number of smokers from approximately 68% to approximately 90%. The average opinion showed a similar increase from approximately 0.75 to 0.92. Lowering the tolerance threshold for those six nodes strongly mitigated the ability for the media node to influence the network. With no educational or counter-marketing campaigns, decreasing the tolerance of the six highest betweenness nodes reduces the average opinion and smoker fractions toward baseline levels steadily, culminating in the lowest set of values when tolerance is set to 0 which corresponds to no opinion propagation across the six nodes.

Effects of Addiction

Above, we outlined a mapping between the opinion of an individual and their behavior using step functions at the initiation threshold and at the cessation threshold. The behavioral function takes on the values [0, 1], equivalent to a false/true distinction when asking if the individual engages in the given behavior. We use a value for an initiation threshold, such that an opinion below the threshold value results in no change, while an opinion equal to or above the threshold value results in the individual initiating the behavior.

The initiation threshold may be interpreted as the minimum value an individual's opinion needs to be in order to choose to assume the costs involved in the behavior. Cost here refers to both the direct and indirect economic costs, as well as the cost in time and effort. The initiation threshold might be raised by raising the purchase price on the item, or by making the item harder to acquire or consume.

The effects of addiction are implemented with the introduction of a cessation threshold. The cessation threshold may be equal to or less than the initiation threshold. If the cessation threshold is less than the initiation threshold, this indicates that the opinion of the individual needs to fall lower than it would otherwise, due to addiction acting as an additional motivating component. Thus, for a strongly addictive product, the cessation threshold could be set at 0.35, versus an initiation threshold of 0.65. This incorporates the fact that, once an individual is addicted, their ability to quit is compromised – their opinion of the product might fall well below the initiation threshold, but they will continue its use. Policies that would make it easier for people to overcome the effects of addiction, such as increasing the availability of nicotine replacement therapy or of smoking cessation counseling, would raise the cessation threshold, making it possible for people to quit smoking at a higher opinion threshold.

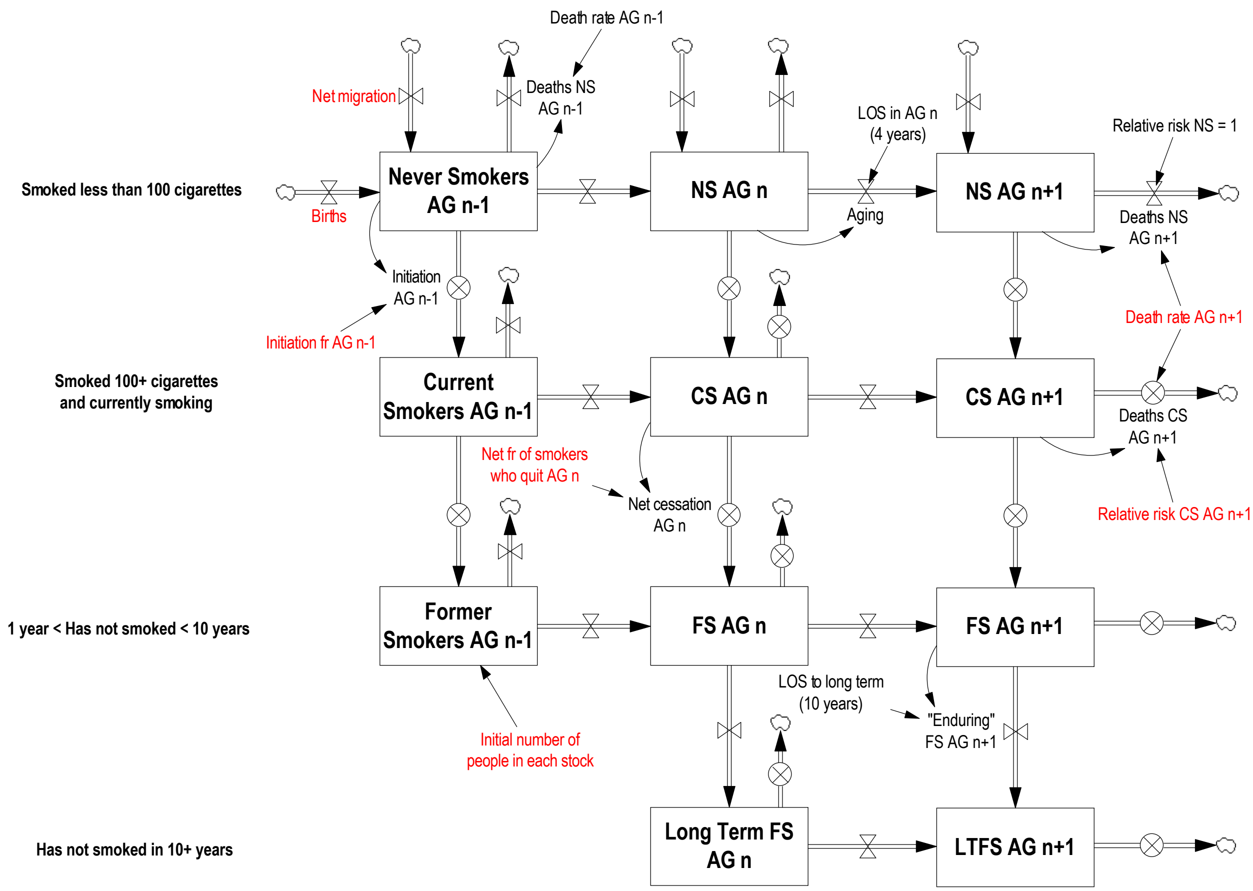


Figure?? Left diagram shows the effect of advertising and educational campaigns on opinion towards smoking and smoking behavior. Advertising is active through t=75. Education campaign starts at t=75, and induces a decrease in average opinion, but has less of an effect on smoking behavior due to hysteresis. Right diagram illustrates percentage of smokers versus average opinion. The number of smokers increases roughly linearly with rising average opinion, but remains fairly level after the average opinion starts to fall.

Integration with System Dynamics Models

The individual based model using bounded confidence opinion dynamics is intended to analyze the effects of policy interventions on community scale populations and on time intervals ranging from months to a few years. The aim is not so much replication of exact historical numbers, but rather a characterization of tendencies and trends resulting from a subset of components involved in lifestyle correlated disease.

Policy analysis that considers the longer term, population scale consequences of interventions needs to integrate additional analytical tools, such as a system dynamics model of a population aging chain.



Figure?? Example aging chain for smoking behavior

The IBM models tobacco use, including initiation and cessation, as a function of individual opinions and opinion dynamics. The effects of interventions can be seen in the changes in model outcomes when the intervention is applied. The results, interpreted as changes in initiation and cessation rates in model populations, can be applied to alter parametric values in a system dynamics model. The system dynamics model can then interpret the results of the intervention on longer time scales.

The system dynamics model can also be used to identify leverage points that can then be investigated in the IBM. If, for example, the SD model were to identify that an intervention resulting in a 25% reduction in initiation rates among adolescents would have a more favorable outcome than other potential interventions, the IBM could be used to predict which initiatives could lead to the desired reduction in initiation.

Conclusions

These analyses demonstrate the value of simple social-network concepts in addressing prevention and treatment of a lifestyle disease. We have shown a plausible mechanism for pro- or anti-tobacco messages to shift the opinions of a population relative to tobacco and eventually to affect the proportion of individuals who smoke. Using our opinion dynamics model, we have shown the effect targeted advertising or educational campaigns where message recipients are selected by their network characteristics such as PageRank and betweenness centralities. We have explored two approaches to imposing changes onto a social network, either through the informational content of the message or through enabling better information propagation through the network. The symbiotic effects of a mixed-message advertising campaign was described, showing how a moderate campaign can be applied to increase the effectiveness of a more extreme campaign. Lastly, we developed a straightforward network model of addiction which demonstrates notional match with observed metrics.

In general, the IBM is intended to consider the effects of interventions as general characterizations, rather than exactly replicating historical data. By looking at dynamics across over a hundred thousand randomly generated networks with randomly generated initial distributions of opinions and behaviors, we can test interventions for robustness across a wide range of different communities and discover the key components for creating robust policies.

1. Hjermann, I., Holme, I., Byre, K.V. & Leren, P. Effect of Diet and Smoking Intervention on the Incidence of Coronary Heart Disease:: Report from the Oslo Study Group of a Randomised Trial in Healthy Men. *The Lancet* **318**, 1303–1310 (1981).
2. Stampfer, M., Hu, F., Manson, J., Rimm, E. & Willett, W. Primary prevention of coronary heart disease in women through diet and lifestyle. *New England Journal of Medicine* **343**, 16-22
3. Single, E., Rehm, J., Robson, L. & Van Truong, M. The relative risks and etiologic fractions of different causes of death and disease attributable to alcohol, tobacco and illicit drug use in Canada. *Canadian Medical Association Journal* **162**, 1669 (2000).
4. Christakis, N.A. & Fowler, J.H. The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* **357**, 370 (2007).
5. Rosenquist, J.N., Murabito, J., Fowler, J.H. & Christakis, N.A. The Spread of Alcohol Consumption Behavior in a Large Social Network. *Annals of Internal Medicine* **152**, 426 (2010).
6. Christakis, N.A. & Fowler, J.H. The collective dynamics of smoking in a large social network. *New England journal of medicine* **358**, 2249 (2008).
7. Glass, L.M. & Glass, R.J. Social contact networks for the spread of pandemic influenza in children and teenagers. *BMC Public Health* **8**, 61 (2008).
8. Smith, K.P. & Christakis, N.A. Social networks and health. *Annual review of sociology* **34**, 405-429 (2008).
9. Dorwin Cartwright, F.H. Structural Balance: A Generalization of Heider's Theory. *Psychological Review* **63**, (1956).
10. Castellano, C., Fortunato, S. & Loreto, V. Statistical physics of social dynamics. *Reviews of modern physics* **81**, 591–646 (2009).
11. Deffuant, G., Neau, D., Amblard, F. & Weisbuch, G. Mixing beliefs among interacting agents. *Advances in Complex Systems* **3**, (2000).
12. Hegselmann, R. & Krause, U. Opinion dynamics and bounded confidence models, analysis, and simulation. *Journal of Artifical Societies and Social Simulation (JASSS) vol* **5**, (2002).
13. Weisbuch, G., Deffuant, G., Amblard, F. & Nadal, J.P. Meet, discuss, and segregate! *Complexity* **7**, 55–63 (2002).
14. Barabási, A.L. & Albert, R. Emergence of scaling in random networks. *Science* **286**, 509 (1999).
15. Albert, R. & Barabási, A.L. Statistical mechanics of complex networks. *Reviews of modern physics* **74**, 47–97 (2002).
16. Jackson, M.O. *Social and Economic Networks*. (Princeton University Press: 2008).
17. Jager, W. & Amblard, F. Uniformity, bipolarization and pluriformity captured as generic stylized behavior with an agent-based simulation model of attitude change. *Computational & Mathematical Organization Theory* **10**, 295–303 (2005).
18. Mokdad, A.H., Marks, J.S., MP, M. & Stroup, D.F. Actual Causes of Death in the United States, 20Ò0. *JAMA* **291**, (2004).
19. Valente, T.W. Social network influences on adolescent substance use: An introduction. *Connections* **25**, 11–16 (2003).
20. Galea, S., Nandi, A. & Vlahov, D. The social epidemiology of substance use. *Epidemiologic reviews* **26**, 36 (2004).
21. Jarvis, M.J. Why people smoke. *British Medical Journal* **328**, 277 (2004).
22. Pierce, J.P., Choi, W.S., Gilpin, E.A., Farkas, A.J. & Berry, C.C. Tobacco industry promotion of cigarettes and adolescent smoking. *JAMA: the journal of the American Medical Association* **279**, 511 (1998).
23. Ling, P.M. & Glantz, S.A. Why and how the tobacco industry sells cigarettes to young adults: evidence from industry documents. *American Journal of Public Health* **92**, 908 (2002).

24. Brin, S. & Page, L. The anatomy of a large-scale hypertextual Web search engine. *Computer networks and ISDN systems* **30**, 107–117 (1998).