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Social Networks and Smoking: Exploring the Effects of Peer Influence and Smoker Popularity Through Simulations

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Abstract

Adolescent smoking and friendship networks are related in many ways that can amplify smoking prevalence. Understanding and developing interventions within such a complex system requires new analytic approaches. We draw on recent advances in dynamic network modeling to develop a technique that explores the implications of various intervention strategies targeted toward micro-level processes. Our approach begins by estimating a stochastic actor-based model using data from one school in the National Longitudinal Study of Adolescent Health. The model provides estimates of several factors predicting friendship ties and smoking behavior. We then use estimated model parameters to simulate the coevolution of friendship and smoking behavior under potential intervention scenarios. Namely, we manipulate the strength of peer influence on smoking and the popularity of smokers relative to nonsmokers. We measure how these manipulations affect smoking prevalence, smoking initiation, and smoking cessation. Results indicate that both peer influence and smoking-based popularity affect smoking behavior and that their joint effects are nonlinear. This study demonstrates how a simulation-based approach can be used to explore alternative scenarios that may be achievable through intervention efforts and offers new hypotheses about the association between friendship and smoking.

Keywords

adolescence, agent-based modeling, network analysis, smoking and tobacco use, systems science

Despite recent declines, smoking remains a major source of preventable premature morbidity and mortality (U.S. Department of Health and Human Services, 2004). Adolescence is a critical period for smoking initiation. In 2009, 46% of high school students report ever having smoked, with 20% of those currently smoking (Centers for Disease Control and Prevention, 2010). Friendship networks are integrally involved on the pathway to smoking (Kobus, 2003). Therefore, understanding the complex social and behavioral processes that lead adolescents to smoke remains a key goal.

Systems science offers hope to improve our understanding of adolescent smoking (Hoffman, Sussman, Unger, & Valente, 2006; Lakon, Hipp, & Timberlake, 2010) and the possible consequences of interventions aimed at preventing smoking initiation and encouraging cessation. Social network analysis in particular shows great potential for investigating the complex social and behavioral dynamics behind smoking (Christakis & Fowler, 2008; Valente, 2010). Using new analytic models, such as the stochastic actor-based model (SABM; also referred to as SIENA), researchers can tease apart friend selection and peer influence processes (Snijders, van de Bunt, & Steglich, 2010; Steglich, Snijders, & Pearson, 2010). The SABM integrates information on smoking and network change to disentangle friends' influence on smoking from selection processes that unite smokers. Notably, this work reveals that similarity in smoking among friends often arises via friend selection, not just through socialization (Kiuru, Burk, Laursen, Salmela-Aro, & Nurmi, 2011; Mercken, Snijders, Steglich, & de Vries, 2009; Mercken, Snijders, Steglich, Vertiainen, & de Vries, 2010b, Mercken, Steglich, Sinclair, Holliday, & Moore, 2012; Schaefer, Haas, & Bishop, 2012; Steglich et al., 2010; Steglich, Sinclair, Holliday, & Moore, 2012). Although such research is informative, it requires longitudinal network data that can be prohibitive to collect (Marsden, 2011).

Another systems science approach—simulations—offers promise in this regard. Simulations are common in health research (Gilbert & Troitzsch, 2009; Homer & Hirsch, 2006) and can be particularly beneficial for

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understanding the impact of manipulating key attributes of complex systems (Homer & Hirsch, 2006; Levy, Mabry, Graham, Orleans, & Adams, 2010; Mabry, Marcus, Clark, Leischow, & Méndez, 2010). In the case of social network models of behavior change, simulations can extend the predictive utility of relatively limited data, when more complex or detailed data collection is not feasible (e.g., Morris, Kurth, Hamilton, Moody, & Wakefield, 2009). In cases where behavioral interventions are common (e.g., smoking), these simulation inputs can be derived from intervention aims and used to estimate potential changes on outcomes of interest (e.g., smoking initiation or cessation).

In contrast to strategies that focus on population-level processes (e.g., Levy et al., 2010), we adopt an agent-based approach that emphasizes micro-level mechanisms that may underlie population-level outcomes. In our case, the SABM represents dynamics underlying the coevolution of peer networks and smoking. Model parameters (or initial conditions) can be altered to investigate how smoking and network coevolution would unfold under different scenarios. For example, we can manipulate parameters that may be amenable to intervention, such as how actors select friends or influence each other through those relationships (Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003). Because parameter estimation in an SABM already incorporates a simulation algorithm, simulating the model with controlled alterations to the model parameters is a natural extension of SABM estimation (Mercken, Snijders, Steglich, Vertiainen, & de Vries, 2010a; Steglich et al., 2010).

Specifically, we manipulate the strength of two model parameters: (a) peer influence (PI) on smoking and (b) smoker popularity. We chose PI because school-based interventions aimed at preventing smoking and other substance use often focus on reducing adolescent susceptibility to PI (Flay et al., 1989; Lynam et al., 1999; Peterson, Kealey, Mann, Marek, & Sarason, 2000). Systematic reviews and meta-analyses find that PI interventions' short- and long-term impacts on smoking have ranged from ineffective to modest and that effects tend to dissipate over time, especially without intervention boosters (Flay, 2009; Hwang, Yeagley, & Petosa, 2004; Lantz et al., 2000; Wiehe, Garrison, Christakis, Ebel, & Rivara, 2005). However, PI manipulation is often one component within a larger behavioral intervention strategy, making nonnull PI effects difficult to disentangle from other effects.

We also manipulate the popularity of smokers relative to nonsmokers. Higher status adolescents are generally more influential than their lower status peers (Brechwald & Prinstein, 2011; Teunissen et al., in press; Valente et al., 2003). Thus, when smokers are more popular than nonsmokers (Killeya-Jones, Nakajima, & Costanzo, 2007; Lakon et al., 2010; Valente, Unger, & Johnson, 2005), the potential for smoking diffusion is high. Accordingly, previous interventions have targeted popular peers or "opinions leaders" (Valente et al., 2003; Valente & Pumpuang, 2007). Other intervention strategies could indirectly affect the popularity of smoking peers by conveying the negative, long-term consequences of smoking, which may stigmatize smoking and, by extension, smokers themselves.

Method

Our objective is to describe how simulations based in the SABM framework can inform intervention efforts. Thus, we draw on SABM results previously reported by Schaefer et al. (2012). We use the same data from the National Longitudinal Study of Adolescent Health to estimate friendship and smoking dynamics among 509 students in one high school. We refer the reader to that study for more detail.

Our approach involves four steps, which we discuss in detail below.

1. Estimate an SABM with observed data to obtain parameter estimates.
2. Identify parameters to manipulate and establish ranges.
3. Simulate network evolution for each combination of parameter values.
4. Record outcome(s) of interest for each simulation run.

SABM Estimation

Here, we describe in overview the SABM that underpins our simulation-based approach. For a fuller description of SABM estimation, see the work of Snijders (2001) and colleagues (Snijders et al., 2010; Steglich et al., 2010). We estimate SABMs and run simulations using RSiena (Ripley, Snijders, & Preciado, 2012).

Estimating an SABM requires data on (a) ties among a set of actors at two or more time points (the network) and (b) behavior measures at the same time points. The model uses two functions to simultaneously evaluate effects hypothesized to be responsible for observed changes. The *smoking function* predicts changes in smoking over time based on individual or peer factors. Of greatest interest here is the effect of PI, which determines whether actors adopt levels of smoking that bring them closer to the average of their friends (the "average similarity" effect within RSiena; see Ripley et al., 2012, for equations). The *network function* predicts changes in network structure over time. Predictors of a tie from one actor to another can include individual and dyadic attributes (e.g., gender, extracurricular activity coparticipation) as well as network processes (e.g., transitivity). In terms of smoking, the likelihood of an $i \rightarrow j$ tie may depend on whether i smokes ("smoke ego"), whether j smokes ("smoke alter"), and the smoking similarity between i and j ("smoke similarity").

In fitting the SABM to observed data, RSiena uses a simulation algorithm to obtain parameter estimates and standard errors. The algorithm begins with the constellation of network and smoking behavior observed at time one, then estimates a series of model parameters that best recreate the network and distribution of behavior observed at one or more subsequent time points. The SABM considers observations at discrete time points as inputs; however, it assumes that changes occur between observations through a series of micro-steps. At any micro-step, one actor can change a tie (i.e., send a new tie or dissolve an existing tie), change smoking behavior by one unit, or make no changes. Actors make the choice that maximizes the value of the respective network or smoking function (with a small amount of random error added to each evaluation). For instance, actors use the smoking function to separately evaluate decreasing, increasing, and maintaining the same level of smoking, then adopt the smoking level that produces the largest value of the smoking function. Opportunities to change ties and smoking behavior are governed by separate rate parameters in each function.

The goal of model fitting is to obtain parameter estimates that best reproduce observed changes in the network and behavior. The model has converged when it produces simulated networks wherein summary statistics match those derived from the observed network (indicated by t statistics <.1 for each effect).

As a first step, we reestimated the model reported by Schaefer et al. (2012) though with one change. To simplify our manipulation, we constrained the effect of smoker popularity to be linear (i.e., by setting the statistically nonsignificant "smoke alter squared" effect to 0). Results do not differ using this model specification (see Table 1). Convergence is good as indicated by the t statistics. In the smoking function, the average similarity parameter representing PI is estimated at 2.89 (SE = .91). The positive valence indicates that actors tend toward their friends' average level of smoking. Turning to the network function, the alter smokes effect, representing smoking-based popularity, was estimated at .14 (SE = .05), indicating that higher levels of smoking were associated with a greater likelihood of being selected as a friend. Finally, though not of immediate interest, the positive smoke similarity effect indicates that students with more similar levels of smoking were more likely to be friends (b = .68, SE = .12).

Parameter Manipulation

We manipulate the PI and smoking-based popularity parameters to observe their effects on smoking outcomes. Several considerations went into identifying a useful range of simulated inputs for each parameter. First, we wanted the ranges to contain 0, indicating the absence of the effect. Second, for smoking-based popularity, we wanted to explore the implications of negative values, which would reflect smokers being *less* popular than nonsmokers. We did not explore negative values for PI, which would imply that actors influence their friends to be different from themselves (i.e., smokers push friends to be nonsmokers and nonsmokers push friends to smoke). Negative peer influence is rare and, to our knowledge, has not been observed in studies of substance use. Last, we extend our manipulated parameters an equal distance in the positive direction. Thus, we consider how smoking would change if there were substantially stronger versions of the observed effects (e.g., stronger influence). With these concerns in mind, PI ranged from 0 to 6 in increments of 1 (which centers on 3, just above the observed value), whereas smoking-based popularity ranged from −.45 to .75 in increments of .15 (centered at .15, close to the observed value).

Simulation

The same simulation algorithm used to fit an SABM can be used to simulate network and smoking coevolution under alternative scenarios. This allows us to explore what would happen if actors followed slightly different rules—such as those introduced by potential interventions. Thus, the simulation approach we propose is a natural extension of fitting an SABM within RSiena. Prior researchers have used this approach to estimate how much smoking homophily is because of socialization versus selecting friends who are already similar (Mercken et al., 2010a; Steglich et al., 2010). Importantly, this process does not involve estimating new model parameters, only exploring the implications of a given set of alternative parameter values.

Our simulation uses the network and smoking behavior of the 509 students observed at Time 1 as initial conditions. Actors are given multiple opportunities to change their network ties and smoking based on the model and parameter estimates from the observed data. We manipulated the PI and smoking-based popularity parameters as described above. All other parameters were held constant at the values estimated from the observed data. We conducted 1,000 simulation runs for each combination of PI and smoking-based popularity values (63 combinations).

Outcomes

As an option, the RSiena package will save the final network and actors' smoking behavior produced by each simulation run. We measure smoking *prevalence* as the proportion of adolescents who smoke at Time 2. In addition, we track how each actor's smoking behavior evolves from that observed at Time 1 to the simulated level at Time 2. This allows us to calculate *initiations* (the proportion of nonsmokers observed at Time 1 who became smokers at Time 2 in the simulation) and *cessations* (the proportions of smokers observed at Time 1 who did not smoke at Time 2 in the simulation). For reference, the observed data indicate that 51.5% and 56.0% of adolescents smoked at Times 1 and 2, respectively; 27.3% of nonsmokers began smoking; and 17.6% of smokers ceased smoking.

Table 1. Estimates From SABM Testing Friendship and Smoking Coevolution.

	b	*SE*	*t*
Smoking function			
Rate	2.06***	.26	.00
Linear shape	−.11	.22	.02
Quadratic shape	1.17***	.16	.02
Female	.16	.19	.02
Age	−.00	.10	.02
Parent smoking	.01	.23	.00
Delinquency	.44**	.16	.01
Alcohol	−.10	.14	.01
GPA	−.09	.13	.01
Average similarity	2.89***	.91	.02
In-degree	−.04	.11	.03
In-degree squared	.00	.01	.03
Network function			
Rate	10.26***	.49	.01
Rate: Truncated roster	−1.18**	.50	.02
Out-degree	−3.91***	.08	.01
Reciprocity	1.91***	.09	.02
Transitive triplets	.52***	.04	.03
Popularity (square root of in-degree)	.29***	.04	.03
Extracurricular activity overlap	.28***	.06	.03
Female similarity	.24***	.04	.01
Female alter	−.11*	.05	.00
Female ego	−.04	.05	.01
Age similarity	1.00***	.13	.00
Age alter	−.01	.03	.00
Age ego	−.04	.03	.00
Delinquency similarity	.15†	.08	.00
Delinquency alter	−.04	.04	.01
Delinquency ego	.02	.04	.00
Alcohol similarity	.27**	.10	.00
Alcohol alter	−.03	.03	.00
Alcohol ego	−.03	.04	.01
GPA similarity	.70***	.13	.01
GPA alter	−.05	.04	.02
GPA ego	−.02	.04	.03
Smoke similarity	.68***	.12	.00
Smoke alter	.14**	.05	.03
Smoke ego	−.04	.05	.04

Note. SABM = stochastic actor-based model.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$ (two-tailed tests).

Results

We begin by describing the results for the PI manipulation, holding the smoking-based popularity parameter constant at its observed value. Figure 1A presents box plots for each value of PI across each outcome. Note that for $b = 3$, which closely corresponds to the observed parameter estimate, the simulated level of smoking prevalence is centered at the observed level, indicating good model fit. The model slightly underestimates the median number of initiations and cessations, though within acceptable bounds.

Examining the range of PI values, we see that as PI increases in strength away from 0, smoking prevalence does not change. Decomposing changes into initiations and cessations also reveals consistent results across the range of PI values. The lack of change suggests that the strength of peer influence has little consequence for smoking outcomes when all other model effects are held constant.

We now consider the consequences of changing the effect of smoking-based popularity, holding PI constant at its observed value (Figure 1B). Again, note that when the coefficient is set at .15, near the observed value of .14, the simulated outcomes closely match the observed outcome. Here we observe more or less linear changes in each outcome across the range of parameter values. As smoking-based popularity increased, smoking prevalence and initiations increased, while cessations decreased. These effects can be interpreted in light of the positive PI effect in the model. Because actors are influenced by whomever they extend ties to, as we manipulate the popularity effect to increase the appeal of smokers as friends, smokers' capacity to influence others increases. Thus, as smoker popularity increases, fewer smokers quit, while more nonsmokers begin smoking.

Last, we consider the implication of manipulating PI and smoking-based popularity in conjunction. Figure 2 presents the results for the three outcomes. In examining the graph for each outcome, note that the bold lines across the middle of each plane refer to the effect of manipulating one parameter while holding the other parameter at its observed value (i.e., they represent the corresponding means from Figure 1).

For all three outcomes, when PI is set to 0, variation in popularity has virtually no impact on smoking outcomes. The results for initiation and cessation indicate that in the absence of PI, actors still change their smoking behavior (due to other model effects). However, the frequency of such changes does not differ based on the popularity of smokers. When friends are not influential, then one's decision whether to smoke or not does not depend on whom one selects as a friend.

However, when PI is present (i.e., positive), its effect on smoking outcomes is moderated by the strength of smoking-based popularity. When smokers are popular, increases in the PI parameter increase smoking prevalence. In contrast, when smokers are unpopular, stronger PI decreases smoking prevalence. Only when smoking-based popularity falls in the range between zero and its observed value do we see little effect of PI on prevalence. These patterns are further understood by examining changes in initiations and cessations. When smokers are popular, increases in PI lead more actors to begin smoking and fewer actors to quit. This pattern is reversed when smokers are unpopular: stronger PI leads to fewer initiations and more cessations. Still, the patterns for initiations and cessations are not mirror images of one

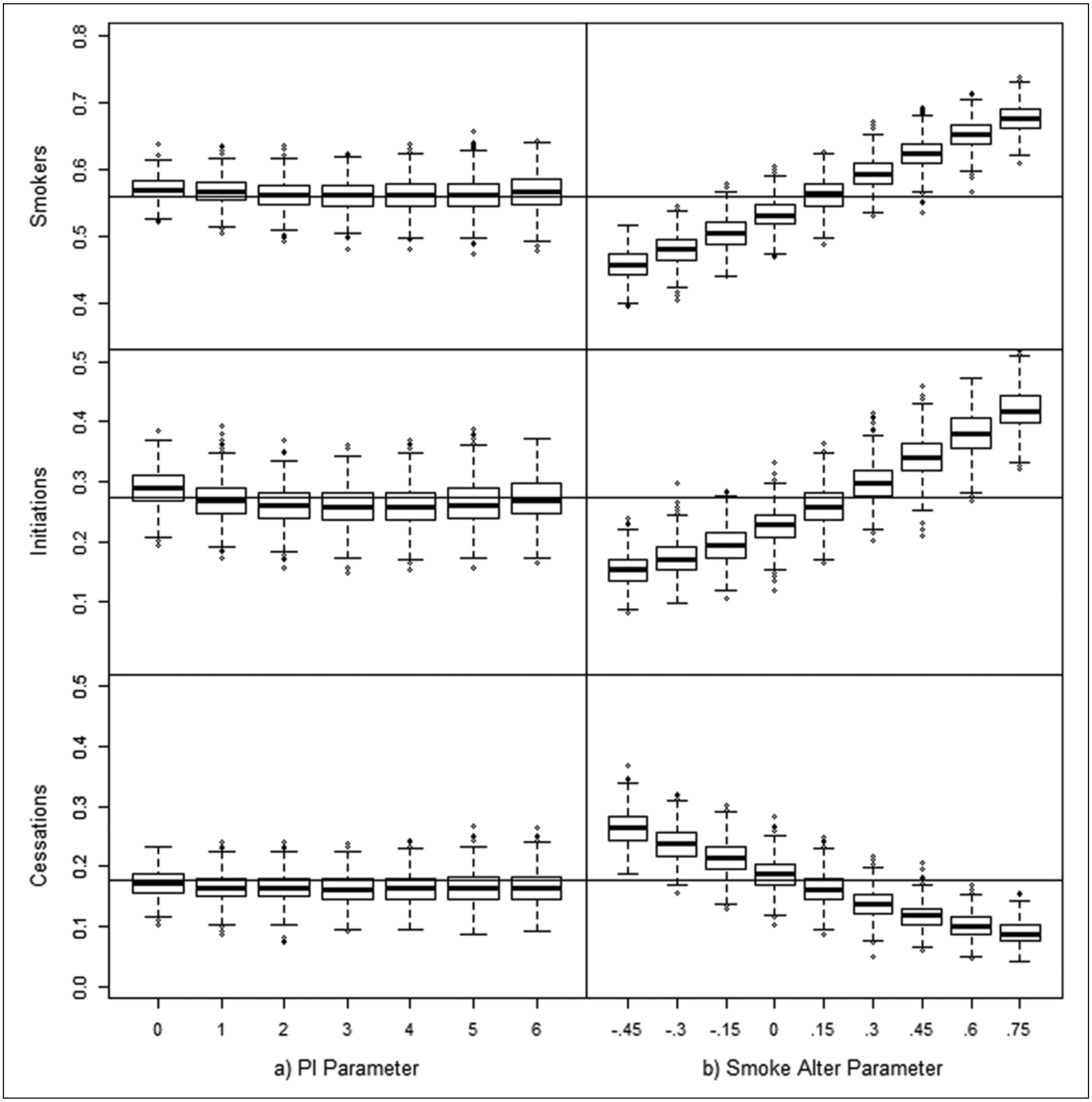

Figure 1. Simulated smoking outcomes based on independent manipulations of peer influence (PI) and smoking-alter (popularity) parameters.[a]

[a]Horizontal lines in each panel represent the observed value of the outcome. "Smokers" is measured as the proportion of adolescents who smoke at Time 2. "Initiations" is the proportion of nonsmokers observed at Time 1 who became smokers at Time 2. "Cessations" is the proportions of smokers observed at Time 1 who did not smoke at Time 2.

another. Changes in PI have a sharper effect on initiations than cessations, as indicated by the steeper slope of the plane for initiations.

In combination, these results suggest that smoking prevalence is affected by the joint values of PI and smoking-based popularity. Smoking prevalence remains near the Time 1 level when PI is absent *or* when smoking-based popularity is absent to slightly positive. This suggests that both PI *and* a nonzero level of smoking-based popularity may be necessary for changes in the other parameter to affect smoking

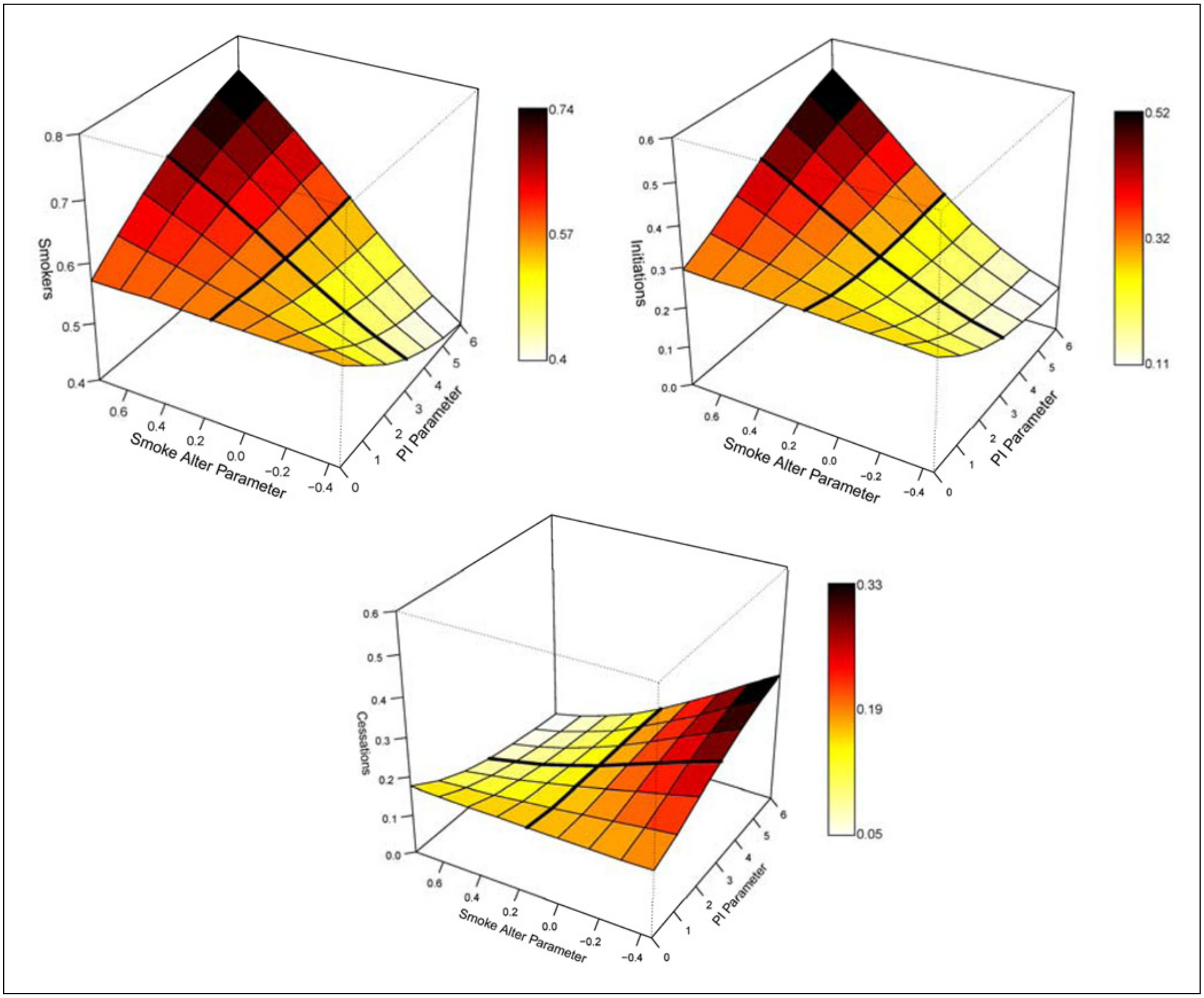

Figure 2. Smoking outcomes based on joint manipulation of peer influence (PI) and smoke alter (popularity) parameters.[a]

[a]Dark lines bisecting each plane coincide with observed values of PI and Smoke Alter parameters. "Smokers" is measured as the proportion of adolescents who smoke at Time 2. "Initiations" is the proportion of nonsmokers observed at Time 1 who became smokers at Time 2. "Cessations" is the proportions of smokers observed at Time 1 who did not smoke at Time 2.

prevalence. Reducing PI should reduce smoking prevalence when smoking contributes to popularity (i.e., the smoking-based popularity parameter is stronger than observed) but not when smoking contributes to unpopularity (i.e., the smoking-based popularity parameter is negative). Reducing the smoking-based popularity effect should reduce smoking prevalence in the presence of PI on smoking.

Discussion

This article demonstrates a novel method to evaluate the potential impacts of behavioral interventions designed to manipulate key attributes of complex systems, such as the coevolution of smoking and friendship networks. Our approach uses an SABM to evaluate hypothetical questions about how changes in the strength of PI and smokers' popularity would affect smoking outcomes at the school level. Simulation results suggest that changes in PI and smoker popularity can affect smoking behavior, but their effects are contingent on one another. Changing smoking-based popularity only affected smoking prevalence when PI was present. Likewise, the impact of changing the PI effect was dependent on the the strength smoker popularity. Higher levels of PI increased smoking when smokers were popular, but decreased smoking when smokers were unpopular. We also observed differences in the impacts of our manipulations on smoking initiation and cessation rates. Manipulating PI and smoker popularity generally had stronger effects for smoking initiation versus cessation. This pattern raises the question of whether friend influence may differ for prolonging smoking versus leading adolescents to smoke. The capacity to generate such new questions is an advantage over other analytic methods and speaks to the utility of our approach.

We manipulated two micro-level mechanisms that link smoking and friendship. These manipulations were based on intervention strategies that commonly target these mechanisms, directly or indirectly, to elicit smoking reductions. However, several additional manipulations are possible, including more refined versions of the effects we considered. We manipulated PI, which can lead adolescents to initiate smoking as well as push them to quit. Yet, many intervention efforts are focused on helping students resist PI on smoking (Wiehe et al., 2005), which is PI in only one direction (i.e., to inhibit initiation). One extension of our approach would be to manipulate the strength of PI for smoking uptake by weakening the influence of friends on smoking initiation. Alternatively, one could manipulate PI on cessation as a means to evaluate possible consequences of cessation programs.

The combined SABM-simulation approach is also flexible enough to incorporate multiple behaviors. For instance, prior research has examined smoking and alcohol use as separate outcomes within the same model (Kiuru et al., 2011). In addition to behaviors, models could include beliefs about smoking, such as intentions to smoke. Thus, one could test for PI on beliefs, versus behavior itself, and how beliefs versus behavior affect friendship dynamics (e.g., de la Haye, Robins, Mohr, & Wilson, 2011). One could also incorporate information on smoking treatment programs as an alternative behavior and model effects of smoking and PI on treatment entry, effects of treatment on smoking, and effects of treatment on friend selection (e.g., whether individuals who have experienced treatment avoid substance users).

Limitations

The primary limitation of our study is that we analyze data from only one school, meaning the findings may not be generalizable. We do not know the extent to which the observed effects are contingent on specific aspects of this context. Of particular note is the relatively high smoking prevalence relative to other Add Health schools. The roles of popularity and influence may diverge in schools with lower initial smoking prevalence (e.g., Alexander, Piazza, Mekos, & Valente, 2001). For instance, if smoking behavior were more clustered in lower prevalence schools (i.e., *higher* levels of smoking homophily), then we may expect less capacity for PI modifications to affect smoking prevalence. In addition, the processes represented by this simulation may vary across school contexts (e.g., the baseline rates of friendship formation or smoking uptake could differ from this school). Although such differences could readily be incorporated into our model, that risks masking possibly important interactions between contextual factors. Thus, extensions of this strategy would be well served to apply the same approach to other schools, to examine how findings shift when contextual factors change, and to identify those effects that remain consistent across a range of contextual situations. This is especially important given the reductions in population smoking prevalence since the collection of the Add Health waves used here.

Part of the reason we used data from the mid-1990s is that collecting high-quality social network data is time and resource intensive (Marsden, 2011). As evidence from models like ours accumulates across a range of schools, we may be able to identify the contextual factors that are necessary to realize desired outcomes from given intervention strategies. Ideally, methods for selecting interventions that are likely to be successful within a given context could be developed based on more readily available data than were necessary for the models we report here.

Our goal was to illustrate how simulations can extend SABM results to evaluate alternative intervention scenarios. We examined friendship and smoking coevolution in only one high school using data that are almost 20 years old and may not reflect the current status of smoking in adolescent culture. Thus, we would not try to generalize these findings to other school/temporal contexts. The extent to which our findings are unique to that specific school context, including initial smoking prevalence, network structure, and the position of smokers and nonsmokers in the network, is an open question. We encourage future use of this method to help answer these and further questions about the implications of intervention efforts in a range of schools. Such research would also help establish the bounds of the PI and smoking-based popularity effects we estimated. Although our simulation considered a broad range of parameter values, it is unknown what magnitude of effect change is achievable through intervention efforts (i.e., we may be overestimating *or* underestimating the plausible intervention effects with the models estimated here).

Conclusions

We introduced a network-based simulation strategy to evaluate the implications of interventions targeting friendship-smoking dynamics. Results suggest that efforts to reduce peer influence and smoker popularity can both reduce smoking prevalence. Despite the inability to generalize our particular findings, we demonstrate a method that can be replicated, and we identify new hypotheses that can be tested in a wider range of schools. We also discussed several steps needed to enable researchers to generalize to a broader range of school contexts. Although one can reasonably estimate the direct effects of intervention efforts on adolescent smoking, our results suggest that examining the underlying mechanisms is important to identify how effects may combine in nonadditive ways. Interventions may affect the behavior of not only the targeted population but also other members of the population to whom they are connected. Thus, as we continue to consider new interventions, future efforts can model their total effects using an approach similar to the one developed here.

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