Published in final edited form as:
Psychol Addict Behav. 2017 November ; 31(7): 763–774. doi:10.1037/adb0000308.

Simulating Drinking in Social Networks to Inform Alcohol Prevention and Treatment Efforts

Kevin A. Hallgren[1], **Barbara S. McCrady**[2], **Thomas P. Caudell**[3], **Katie Witkiewitz**[2], and **J. Scott Tonigan**[2]

[1]University of Washington, Department of Psychiatry and Behavioral Sciences

[2]University of New Mexico, Center on Alcoholism, Substance Abuse, and Addictions

[3]University of New Mexico, Department of Electrical and Computer Engineering

Abstract

Adolescent drinking influences, and is influenced by, peer alcohol use. Several efficacious adolescent alcohol interventions include elements aimed at reducing susceptibility to peer influence. Modeling these interventions within dynamically-changing social networks may improve our understanding of how such interventions work and for whom they work best. We used stochastic actor-based models to simulate longitudinal drinking and friendship formation within social networks using parameters obtained from a meta-analysis of real-world 10th grade adolescent social networks. Levels of social influence (i.e., friends affecting changes in one's drinking) and social selection (i.e., drinking affecting changes in one's friendships) were manipulated at several levels, which directly impacted the degree of clustering in friendships based on similarity in drinking behavior. Midway through each simulation, one randomly-selected heavy-drinking actor from each network received an "intervention" that either: (1) reduced their susceptibility to social influence, (2) reduced their susceptibility to social selection, (3) eliminated a friendship with a heavy drinker, or (4) initiated a friendship with a non-drinker. Only the intervention that eliminated targeted actors' susceptibility to social influence consistently reduced that actor's drinking. Moreover, this was only effective in networks with social influence and social selection that were at higher levels than what was found in the real-world reference study. Social influence and social selection are dynamic processes that can lead to complex systems that may moderate the effectiveness of network-based interventions. Interventions that reduce susceptibility to social influence may be most effective among adolescents with high susceptibility to social influence and heavier-drinking friends.

Keywords

adolescent drinking; computer simulation; social influence; social selection; socialization

Drinking levels of adolescents tend to be associated with the drinking levels of their peers (Andrews, Tildesley, Hops, & Li, 2002; Leung, Toumbourou, & Hemphill, 2014; Meisel et

Corresponding author: Kevin A. Hallgren, 1959 NE Pacific Street, Box 356560, Seattle, WA 98195. Phone: 206-616-2906. Fax: 206-543-9520. khallgre@uw.edu.

al., 2015). This association is often attributed to social influence, where the drinking of individuals affects the drinking of their friends (Kelman, 1958), and social selection, where individuals are more likely to create and maintain friendships with people who drink similarly to themselves (Verbrugge, 1977). Social influence and selection can operate simultaneously (Huang et al., 2014; Mathys, Burk, & Cillessen, 2013; Mercken, Steglich, Knibbe, & de Vries, 2012; Parra et al., 2007) and the relative strength of each mechanism can vary based on individual differences between adolescents (e.g., drink-refusal skills, age) and their parents (e.g., parental support and monitoring; Fairlie, Wood, & Laird, 2012; Mercken et al., 2012; van der Vorst, Engels, & Burk, 2010).

The directional effects of social influence and social selection are reciprocal: with social influence, one's friends affect their drinking, and with social selection one's drinking affects who they select as friends. Both mechanisms operating simultaneously can create feedback loops that can result in systems with dynamic and nonlinear properties. In the case of positive feedback, small changes in one part of the system can become amplified over time: for example, one person increasing their drinking could lead that person to select more friendships with heavier drinkers (due to social selection), which in turn could further reinforce that person's heavy drinking (due to social influence). Feedback can similarly lead to self-organizing network dynamics, such as the formation of friendship clusters based on similarity in drinking or hobbies (Barnett, Ott, Rogers, Loxley, Linkletter, & Clark, 2014).

Social influence may operate in several ways, including through behavioral modeling, overt encouragement for drinking, covert reinforcement of drinking, and by biasing perceived drinking norms (Borsari & Carey, 2001). Reducing susceptibility to social influence has been a primary component of many adolescent prevention and treatment programs (Larimer & Cronce, 2007; Prestwich et al., 2016; Tebb et al., 2016). For example, enhancing adolescents' drink-refusal skills could help them decline alcohol when they associate with friends who drink heavily, reducing the impact of social influence on the person receiving such interventions. Reducing adolescents' over-inflated estimates about the frequency and intensity of their peers' drinking could also reduce the impact of social influence, particularly if perceived norms become more biased as their friends drink more heavily. Likewise, parent-based interventions often include components aimed at reducing susceptibility to social influence, for example, that encourage parents to monitor adolescent activities and communicate strategies for handling social pressure to drink (Turrisi, Jaccard, Taki, Dunnam, & Grimes, 2001; Wood et al., 2010). Twelve-step treatment models likewise encourage the development of larger pro-abstinent social networks to offset the influence of, and susceptibility to, pro-drinking social networks (Chi, Kaskutas, Sterling, Campbell, & Weisner, 2009; Kelly, Stout, & Slaymaker, 2014).

Researchers increasingly have called for greater understanding of how and for whom existing interventions work. This is especially complicated for network-based interventions given that environments in which they are embedded are dynamic and cannot be experimentally controlled (Galea, Hall, & Kaplan, 2009; Hunter-Reel, McCrady, & Hildebrandt, 2009; Latkin & Knowlton, 2015; Leonard, 2015). Advancements in longitudinal social network analysis (Latkin & Knowlton, 2015) and computer simulation modeling (e.g., Bahr, Browning, Wyatt, & Hill, 2009; Sánchez, Villanueva, Santonja, &

Rubio, 2011; Schaefer, Adams, & Haas, 2013) have provided frameworks for systematically understanding and testing social network models of health behaviors that are challenging to model or impractical to control in real-world settings. Longitudinal social network analysis comprises a broad set of methods for modeling how social ties (e.g., friendships) and attributes of individuals (e.g., drinking statuses) change over time and in an inter-related manner (e.g., due to social influence and social selection). Rather than modeling subjects as independent from one another and randomly sampled from a larger population, participants are modeled as *inter*dependent with one another and the full configuration of social relationships between the persons being studied is prioritized within the analysis. Several researchers have used longitudinal social network analysis to study adolescent drinking and generally have found consistent evidence of social selection with mixed evidence of social influence (e.g., Cheadle, Walsemann, & Goosby, 2015; Huang et al., 2014; Mundt, Mercken, & Zakletskaia, 2012; Wang, Hipp, Butts, Jose, & Lakon, 2016). This work has also identified factors that moderate these effects; for example, Wang et al. (2016) found that home drinking environments and general support offered by parents reduced susceptibility to social influence, such that the correlation between having many heavy drinking friends and subsequent heavier drinking was weaker for adolescents whose families drank less or whose parents were offered more general support.

Social network analysis can be extended by using simulation methods to model friendships and drinking dynamics via computer modeling. Rather than collecting real-world data, these models test hypothetical behavioral outcomes under a set of assumed conditions about how social networks and behavior change over time. Although simulation methods necessarily simplify the complexities of real-world behaviors and network dynamics, they can nonetheless provide theoretical insight into social and behavioral phenomena by controlling the parameters that guide behavior and manipulating them in ways that may not be possible in the real world. For example, Braun, Wilson, Pelesko, Buchanan, and Gleeson (2006) showed that social influence could cause alcohol cessation interventions to spread to other non-targeted network members, with the degree of this spreading differing based on the configuration of each network, although their simulations were limited such that social ties were static over time (i.e., no changes in friendships). Fitzpatrick, Martinez, Polidan, and Angelis (2016) used agent-based modeling to simulate how groups and drinking evolve within a single drinking episode (i.e., parties with 20 actors) and showed that hypothetical changes in drinking self-identity could result in small but consistent reductions in drinking in these social contexts. Schaefer et al. (2013) used parameters derived from real-world adolescent networks to simulate a population-level intervention that reduced social influence and reduced the popularity of smokers, which in turn reduced the onset of tobacco use. However, we are aware of no studies that have simulated adolescent drinking in networks with social influence and social selection interacting simultaneously. Additionally, existing studies have only tested the impact of interventions conducted at the population level (e.g., interventions that reduce social influence for an entire network) but not the individual level (e.g., interventions that reduce social influence for a single person targeted for intervention).

In the present study, we used computer simulations of social networks to model longitudinal changes in drinking and friendships. In particular, we modeled how drinking may change in response to different individual-focused alcohol interventions within the context of dynamically-changing social networks. Social influence and social selection were systematically manipulated across the networks to understand how these effects impact heavy drinking rates and friendship clustering. Then, the impacts of different network-related strategies for reducing adolescent alcohol use were tested by subjecting a single heavy-drinking actor within these networks to different social network-related interventions. The aim of this work is to better understand how social influence and social selection affect adolescent drinking and friendships, and to better understand how network-based interventions may be more efficacious within different social contexts.

Method

Overview

In the following sections, we first introduce the real-world reference study that provided the parameters used for guiding our simulations, then qualitatively describe the procedure for simulating how actors change their drinking and friendships over time. We then describe the experimental procedures for manipulating levels of social influence and social selection, the network based alcohol interventions that were assigned to targeted actors, and the analytic plan for assessing the outcomes of interest (e.g., friendship clustering, intervention effectiveness).

Reference Study

Simulation parameters were derived from a meta-analysis of five longitudinal social network studies of southern California 10th graders (Huang et al., 2014). The reference study followed a mean of N=287 adolescents in each high school social network (total of 1434 adolescents) over a seven-month period. Up to 19 friends were identified by each adolescent (mean = 5.17 friendships per adolescent) by identifying specific friends from a photo roster of students in their grade. Drinking statuses were coded on a 5-point composite scale based on drinking intentions over the subsequent year (1 = not susceptible/no intention to drink, 2 = susceptible/any intention to drink) and past drinking behavior (3 = ever drank, 4 = past-month drinking, 5 = past-month binge drinking). Using stochastic actor-based models (SABMs; described below), Huang et al. estimated several parameters for modeling how friendships, drinking, smoking, and social network media use changed over time, and their results provided evidence for alcohol-related social influence and social selection operating simultaneously. Only the friendship- and drinking-related parameters from the reference study were modeled in the present study (i.e., smoking, demographic, and social media variables were not modeled).

Stochastic Actor Based Models (SABMs)

Drinking and social networks were modeled using SABMs of social networks (Snijders, 1996, 2001; Snijders, van de Bunt, & Steglich, 2010). SABMs are particularly useful for studying longitudinal changes in network ties (e.g., friendships) and actor characteristics (e.g., drinking statuses) under conditions where network ties and actor (i.e., person) characteristics are assumed to change relatively slowly and represent status-like variables (e.g., drinking status over a period of weeks or months) rather than changing quickly and represent momentary variables (e.g., drinks consumed with friends during a single drinking episode; e.g., Fitzpatrick et al., 2015).

SABMs have several assumptions about the nature of social networks and the actors within them. First, SABMs are stochastic, meaning that changes in friendships and drinking statuses are modeled probabilistically rather than deterministically (i.e., no specific changes are guaranteed based on a given set of input conditions, but some changes are more likely to occur than others). Second, SABMs assume that longitudinal changes in social networks are Markov processes, where the state of the system at time $t + 1$ is predicted only by the state of the system at time t. In other words, changes in the system are only influenced by the current state of the system, and relevant information about historical states (e.g., $t - 2$) are either assumed to be encoded within the current system state (t) or assumed to be uninfluential in affecting future states of the system. Third, SABMs assume that friendships between actors are not necessarily bidirectional; that is, an actor who receives a tie from another actor does not need to reciprocate this tie (i.e., actor i may consider actor j to be a friend, regardless of whether actor j reciprocates this friendship); nonetheless, most networks do exhibit reciprocity effects (discussed below) that make many friendships likely to be reciprocated. Fourth, SABMs weigh all social ties equally (i.e., they do not differentially prioritize some social relationships as more influential or important than others).

An objective function guides the longitudinal changes in friendships, and the terms (i.e., effects) within the objective function are specified by the researcher (see Snijders et al., 2010 for detailed overview and mathematical foundations). Several effects are common in guiding friendship choices within social networks: for example, most social networks have a negative *outdegree effect*, or a tendency for actors to extend a relatively low number of friendships relative to the number of friendships that could potentially exist. Networks often have a positive *reciprocity effect*, or a tendency for an actor i who is the recipient of a friendship from actor j (i.e., $j \rightarrow i$) to reciprocate friendship back to that actor ($i \rightarrow j$). Holding all other variables constant, the reciprocity effect also makes a bidirectional relationship (i.e., $i \leftrightarrow j$) more likely to be sustained over time than a unidirectional relationship ($i \rightarrow j$). A positive *transitivity effect* also is common in most networks and describes the tendency for actors to become friends with friends-of-friends ($i \rightarrow h$, given that $i \rightarrow j \rightarrow h$) more often than they become friends with distantly-related or unrelated individuals. Many networks also have a negative *three-cycle effect*, describing the tendency for actors to avoid cyclical tie patterns (e.g., if $i \rightarrow j$ and $j \rightarrow k$, then it is less likely that $k \rightarrow i$) because friendship networks tend to have some degree of hierarchical ordering corresponding to social status (Snijders et al., 2010).

A separate objective function models changes in behaviors. A *linear shape effect* models whether a behavioral variable, such as drinking, tends to be endorsed at the lower (negative linear shape effect) or higher end of the measurement scale (positive effect). A *quadratic shape effect* reflects the impact of a behavioral variable on itself, for example, indicating whether an increase in drinking behavior tends to precipitate additional increases in drinking (i.e., drinking is self-reinforcing; positive quadratic shape effect) or precipitate subsequent reductions in drinking (i.e., drinking is self-correcting; negative effect).

Social ties and actor attributes can also mutually affect one another. For example, social influence (*average alter effect*) can be incorporated into the behavioral objective function to model the extent to which actors change their own drinking to become more similar to the average drinking of their immediate friends. Social selection (*similarity effect*) can be incorporated into the friendship objective function to model the extent that actors are more likely to extend and maintain friendships to others who have similar drinking statuses while being less likely to do this with actors who have dissimilar drinking statuses.

For real-world longitudinal network data, the RSiena program (Ripley et al., 2013) uses a simulation-based estimation procedure to quantify the direction and magnitude of each of these friendship and behavioral effects for a longitudinal network dataset. The same estimation procedure can be used to simulate hypothetical social network data based on a pre-specified set of friendship and behavioral effects (Snijders, 2010), as was done in the present study. In both cases, the program simulates a sequence of micro-steps in which individual actors sequentially make a series of single changes to one of their friendships or their drinking status. In brief, a single actor is randomly selected and then every possible change they could make to each of their friendship ties is considered (e.g., the actor can redact any currently existing friendship, add a new friendship where one does not exist, or make no changes to any friendships). The likelihood of making each of these changes is evaluated using a procedure analogous to multinomial logistic regression, where friendship changes that lead to greater consistency with the parameters specified by the friendship objective function (e.g., those that lead to levels of reciprocity, transitivity, social selection, etc. that are closer to their specified parameter values) have higher probabilities of occurring. One outcome is selected using a random number generator, with the likelihood of each outcome weighted by the probability computed in the previous step. The process is then repeated many times, with a *friendship rate effect* indicating the average number of times each actor is selected for considering such friendship changes over the observation period. A similar process occurs concurrently for behavioral effects (i.e., computer selects a network member, computes the relative probability of making each possible change in their drinking status, then selects a specific change).

Experimental Design

Network effects—All simulated networks were specified to have similar or identical[1] parameters as those obtained in the reference study, including friendship effects (outdegree, reciprocity, transitivity, three-cycle, and friendship rate) and drinking behavior effects (linear drinking, quadratic drinking, and drinking rate effects). Levels of social influence were manipulated to be 0, 1, 2, 3, or 4 times higher than the reference study, and these conditions were crossed by social selection manipulations that were 0, 1, 2, and 3 higher than the reference study[2]. The complete set of parameter values are listed in Table 1.

[1]Increasing the level of social selection (discussed below) increased the number of outgoing ties above the reference study's mean of 5.17 friendships per actor. Outdegree effects were therefore downwardly adjusted slightly from the reference study and calibrated across levels of social selection to produce networks with approximately 5.17 friendships per actor. See Table 1.

[2]Increasing social selection beyond this level resulted in networks that were highly unrealistic, for example due to extremely high variance in the number of friendships per person (e.g., sometimes over fifty friendships per person), which could not be corrected by reducing outdegree effects.

Simulation process—The process by which networks were initialized, evolved, and manipulated is illustrated in Figure 1. Networks were first initialized by randomly assigning drinking statuses and friendships to the 287 actors in each network (only five are shown in Figure 1 for illustrative purposes), with the initial number of friendships and distribution of drinking statuses matching those obtained in the reference study but the structures of the networks being completely random (e.g., Figure 1, panel A). Then, networks evolved according to the friendship and drinking effects described above[3]. The purpose of this first evolution was to create networks with friendship and drinking structures (e.g., reciprocity, transitivity, etc.) that were more reflective of the specified network and drinking effects (see Figure 1, panel B) instead of their initially random configurations. Then, one randomly-selected network member with the heaviest observed drinking level (i.e., usually 5 on the 1-to-5 scale) was identified as the target for intervention. To subject the same actor to different types of interventions, five identical copies of the network were created, and in each copy the same heavy-drinking target actor was selected and subject to a different intervention (described below; see Figure 1, panel C). Each copied network then evolved again after the intervention took place following the specified friendship and drinking effects, imitating drinking and friendship evolution that may be expected to occur over the 7-month period reflected in the reference study. At the end of the simulation, the drinking statuses for the targeted actor were recorded to determine whether the intervention impacted the target actor's drinking outcome (Figure 1, panel D). This process was then repeated over 500 trials for each combination of conditions.

Interventions—The interventions tested were based on theories of social influence, which suggest that drinking may be reduced by decreasing susceptibility to social influence, increasing one's contact with lighter-drinking or abstaining friends, or decreasing one's contact with heavier-drinking friends. The first intervention eliminated the target actor's susceptibility to social influence, making that actor's drinking behavior independent of the drinking of their friends (however, the amount of social influence acting on other actors who were not targeted for intervention remained unchanged). This manipulation was modeled after real-world interventions that reduce the impact of heavy-drinking friends on one's own alcohol use (e.g., by enhancing drink-refusal skills) without directly changing their friendships. The second manipulation eliminated the target actor's susceptibility to social selection, making the target actor's friendship formation independent of the similarity between their own drinking and their friends' drinking. This manipulation is not directly representative of real-world interventions, but was included here in light of the consistent evidence of social selection as a prominent mechanism in adolescent networks. The third manipulation created a new tie from the target actor to a randomly-selected non-drinking actor, whereas the fourth manipulation removed an existing tie from the target actor to one heavy-drinking actor. These interventions were modeled after strategies that focus on increasing contact with non-drinkers and decreasing contact with heavy drinkers, for

[3]Following the recommendation of Snijders (2010), rate parameters were multiplied by a factor of 5 for the first wave of network evolutions to allow actors many opportunities to change their friendships and drinking statuses. This allowed the simulated networks to more effectively change from a completely random configuration to a configuration that was representative of their specified drinking and friendship parameters.

example through mutual support groups, encouraging new friendships with non-drinking network members, or reducing contact with heavier drinking friends.

Analytic Plan

Statistical analyses first examined the impact of social influence and social selection on friendship clustering (i.e., individuals having similar drinking statuses as their friends). Clustering was assessed for each network by computing the Pearson correlation between each actor's drinking status and the average drinking statuses of their friends. This was computed at the conclusion of each network simulation, using control condition data only (i.e., panel D in Figure 2, excluding the four networks that received an intervention). The correlation coefficients that reflected clustering by drinking status for each network were then entered into a multiple regression model and predicted by the simulation parameter values of social influence, social selection, and the social influence × social selection interaction that generated them to test the additive and interactive impact of social influence and social selection on clustering.

The effects of the four interventions on target actors' subsequent drinking outcomes were evaluated using linear mixed-effects regression analysis (Bates, Mächler, Bolker, & Walker, 2015). Treatment conditions were dummy coded to test whether their effects on target actors' post-intervention drinking outcomes were significantly different from the control condition. Copies of the same networks within each instance of the simulation were modeled as nested factors by treating each trial as a random effect. Omnibus interaction tests first evaluated whether the effect of each treatment vs. control was different across levels of social influence or social selection. These were followed by main effects tests of each intervention compared to the control condition within each combination of social influence and social selection. Subsequent analyses then tested whether intervention effects were moderated by the average drinking statuses of target actors' friends at the time of the intervention to understand the conditions under which different interventions may be most effective (i.e., is an intervention more effective for individuals who are embedded in heavier-drinking friendship clusters?). The R lme4 package (Bates et al., 2015) was used for linear mixed-effect modeling. *P*-values were adjusted using Bonferroni correction (*p*-values multiplied by 4) to reduce type-I errors associated with having four tests of significance within each combination of network-level effects. Due to the large volume of results, presentation of the findings in the present study is focused on describing the patterns of results rather than drawing conclusions from the findings within each specific combination of conditions.

Results

Clustering by Drinking Status

The impact of social influence and social selection on friendship clustering is displayed in Figure 2. These results show the mean correlations between actors' drinking statuses and the average drinking statuses of their friends (*y*-axis) for each combination of social influence (*x*-axis) and social selection (separate lines). There was almost no clustering by drinking status when social influence and social selection were both absent (mean $r = -.01$).

Clustering increased monotonically and reached small-to-medium effect sizes when social influence increased but social selection was zero (mean r = .06 to .22) and when social selection increased but social influence was zero (mean r = .16 to .38). Clustering effects were typically largest when both social influence and social selection were simultaneously present (mean r = .23 when social influence and social selection matched the reference sample, increasing to mean r = .71 at the highest levels of social influence and social selection). There was a small but significant social influence × social selection interaction on clustering, such that simultaneously increasing both effects yielded an increase in clustering (B=0.11, SE=0.007, p<.001) beyond the main effects of social selection (B=0.32, SE=0.003, p<.001) and social influence alone (B=0.28, SE=0.005, p<.001).

Figure 3 displays four example social networks from different simulation conditions with increasing levels of social influence and social selection. The networks in this figure illustrate how drinkers generally were distributed evenly throughout the example network with zero social influence and zero social selection (top left panel) and that the tendency for clustering increased as social influence and social selection increased (remaining panels). For example, the bottom panels, which have two- and three-times higher social influence and social selection effects than the reference study, illustrate increasing separation of actors based on their drinking statuses (i.e., separation of darker and lighter nodes) along with higher numeric values representing clustering (Pearson correlations displayed in each graph).

Histograms below the four example networks (Figure 3) illustrate the distributions of drinking statuses for the actors in each example network. At lower levels of influence and selection, most actors tended to have abstinent and lighter drinking statuses (e.g., scores of 1 to 3 on the 5-point Likert-type drinking scale). However, as social influence and social selection increased, the distribution became more bimodal as the number of actors with the lowest (1) and the heaviest levels of drinking (5) increased and the number of actors with intermediate drinking statuses (2 to 4) decreased. This pattern was consistently found across other simulation conditions in addition to those shown here. Together, these indicate that there was increasing polarization of drinking behaviors (i.e., actors being more likely to adopt the highest and lowest drinking values) that co-occurred with polarization of friendship clustering (i.e., heavy drinkers mostly having heavy-drinking friends and abstainers/lighter drinkers mostly having abstainer/lighter-drinking friends) due to increasing social influence and selection.

Intervention Effects on Target Actor Drinking

Analyses next tested whether targeting a randomly-selected actor for network-based interventions significantly impacted their subsequent drinking status. An omnibus test of treatment condition × social influence level × social selection level on target actor drinking outcomes was significant, $\chi^2(4)$=18.9, p=.001, indicating that the effect of the treatment manipulations differed across combinations of social influence and selection. Follow-up tests indicated that two of the four interventions had effects that specifically varied across combinations of social influence and social selection, including treatment that eliminated susceptibility to social influence, B=−0.40, SE=0.10, t=−3.87, p<.001, and treatment that eliminated susceptibility to social selection, B=−0.26, SE=0.10, t=−2.54, p=.01.

The effects of these interventions were further probed by evaluating the treatment main effects (relative to control) within each combination of social influence and social selection. These results are shown in Figure 4, which displays the average drinking statuses of target actors at the conclusion of the simulation (y-axis) for each treatment condition (separate bars in each graph). The 4 × 5 grid of plots shows results across varying levels of social selection (rows, increasing from top to bottom) and social influence (columns, increasing from left to right).

Reducing the target actor’s susceptibility to social influence (condition labeled “Infl” in Figure 4) was the intervention most commonly associated with reduced target actor heavy drinking relative to the control condition (labeled “Ctrl”). Specifically, this reduction occurred only in networks with social influence that was at least two times higher than the reference sample and networks with social selection that was at least as high as (but often higher than) the reference sample. More generally, the pattern of results indicated that this manipulation typically exerted the greatest effects when social influence and social selection were considerably higher than the values obtained by the reference sample.

Reducing the target actor’s susceptibility to social selection (labeled “Sel” in Figure 4) reduced the target actor’s drinking on one occasion when social selection and influence were three and four times the levels obtained by the reference study, which were also the highest levels of these effects that were tested in the present study. Adding a friendship to a non-drinker (labeled “+tie”) and removing a tie from a heavy drinker (“−tie”) did not significantly reduce drinking outcomes in any of the conditions.

Moderating Effect of Pre-Treatment Ties to Heavy Drinkers

Moderation analyses tested whether the effects of the interventions were dependent on the extent to which an actor’s friends drank heavily at the time of the intervention. Figure 5 plots the associations between drinking outcomes for target actors at the end of the simulation (y-axis) and the mean level of drinking among the actors’ friends at the time of intervention (x-axis). The strengths of association between pre-treatment friends’ drinking and post-treatment target actor drinking are indicated by the slopes of the diagonal lines for each treatment condition. The control conditions are plotted as dashed lines, and only treatment conditions with significantly different slopes from the control condition are labeled to enhance readability of the figure. (Histograms of the average drinking statuses of the target actor’s friends are included at the bottom of each graph to contextualize the distributions of the average pre-treatment drinking statuses of targeted actors.) Reducing target actors’ susceptibility to social influence was the only experimental condition that had a treatment effect that was moderated by friends’ pre treatment drinking statuses (lines labeled “Infl” in Figure 5). This moderation effect was present in four combinations of social influence and social selection. In each case, social influence was at least three times higher than the reference sample and social selection was at least as high as the reference sample. Slopes for the associations between ties to heavy drinking actors at the time of the intervention and the targeted actors’ drinking outcomes were approximately zero (all p≥.12) in the intervention that eliminated susceptibility to social influence. In contrast, slopes in the other conditions, including the control condition, were increasingly positive as levels of social influence and social selection in the social networks increased. Additionally, the difference in actor drinking outcomes between the social influence intervention and the control condition was most pronounced for actors whose friends were the heaviest drinkers. In other words, as social influence and social selection increased, having more heavy drinking friends was associated with an increasingly greater likelihood of target actors maintaining their heavy drinking statuses over time in the control condition (i.e., positive slopes). In contrast, participants who underwent the intervention that eliminated their susceptibility to social influence no longer had drinking outcomes that were predicted by the drinking statuses of their friends at the time of intervention (i.e., flat slopes) and the greatest effect of the social influence intervention on drinking outcomes, compared to control, (i.e., vertical distance between lines) was found for actors whose friends drank most heavily.

Discussion

The present study simulated longitudinal social networks that were modeled after the friendship and drinking dynamics of 10^{th} graders from Southern California high schools (Huang et al., 2014). We examined the impacts of social influence and social selection on friendship clustering and drinking behavior and the impacts of four network-based intervention strategies within different social environments.

Increasing the degree of social influence and social selection increased the tendency for friendships to “cluster” based on similarity of drinking behavior. The strongest degree of clustering was present when both social influence and social selection were present simultaneously and were at high levels. Increasing social influence and social selection also led to drinking behaviors becoming increasingly bimodal, with more individuals being at the highest and lowest levels of drinking and fewer individuals having intermediate levels of drinking. This polarization in both friendship ties (i.e., clustering) and drinking behavior (i.e., bimodal drinking distributions) is likely explained by the feedback loop created from actors’ friendships affecting their drinking (social influence) and their drinking simultaneously affecting who they have as friends (social selection). For example, a high level of social selection is expected to cause heavier drinkers to create more friendships with other heavy drinkers while also eliminating existing friendships with lighter drinkers and abstainers. In turn, a high level of social influence may further cause these friends to reinforce that person’s heavy drinking. More generally, these findings suggest that social selection and social influence are sufficient conditions for creating networks that self-organize around drinking behavior, wherein an initially random distribution of drinking behaviors and social ties can become increasingly polarized in drinking behavior and friendship structure over time due to positive feedback (Bertalanffy, 1968). Of note, the strongest amount of clustering was observed in conditions where social influence and social selection were much higher than likely real-world values (i.e., several times larger than the magnitudes observed in the reference study); therefore findings from these conditions may best be interpreted as providing theoretical support for such feedback leading to self-organized clustering around similarity in drinking behavior, rather than precise reflections of specific networks in the real world.

Several social network-based intervention approaches were tested for their efficacy in reducing the drinking of randomly-selected, heavy-drinking target actors. Treatment manipulations that reduced target actors' susceptibility to social selection, added a tie to a nondrinker, or removed a tie from a heavy drinker did not consistently reduce target actor drinking in these simulations. The only intervention that significantly reduced the target actors' drinking across multiple types of networks was the intervention that eliminated their susceptibility to social influence. Importantly, moderation analyses showed that this manipulation only was effective at reducing heavy drinking in networks that had higher levels of social influence and social selection than what was found within the reference sample and was most effective for actors with heavier-drinking friends. This suggests that interventions that reduce susceptibility to social influence may have less effect if applied indiscriminately to heavy-drinking adolescents and more effect if they specifically target adolescents who are highly susceptible to social selection and social influence, especially for adolescents with many heavy-drinking friends. In light of this, future prevention and treatment efforts may wish to focus on improving methods to identify specific adolescents that are more susceptible to social selection and social influence and methods to increasingly target these adolescents in alcohol interventions.

Reducing an individual's susceptibility to social influence may disrupt the effect of their heavy-drinking friends on their own drinking, allowing them more opportunity to change their drinking status even if they have many friends who drink heavily. In contrast, reducing social selection, adding a tie to a non-drinker, or removing a tie from a heavy drinker may have minimal impact on drinking outcomes based on social network dynamics alone, especially if a person has many heavy-drinking friends. When social influence and social selection create highly clustered networks, these interventions may be insufficient to provide significant enough changes in one's social environment to subsequently affect their drinking without the additional influence of outside factors that were not modeled here. That is, even after defriending a heavy drinker or befriending a non-drinker, a heavy-drinking person may still have several other friendships with heavy drinkers who continue to reinforce heavy drinking, and such a person may need additional intervention beyond these to effectively change their drinking. Other social network dynamics that are unrelated to alcohol use, such as reciprocity (i.e., the tendency to maintain friendships with people who consider the actor their friend) and transitivity (i.e., the tendency to maintain friendships with friends-of-friends) may also help keep an individual embedded within their heavy-drinking social environment, making subsequent reductions in drinking less likely. Making more substantial changes to social networks (e.g., eliminating all friendships with heavy drinkers or adding ties to multiple non-drinkers) could lead to stronger effects than the interventions shown here. However, network changes of that magnitude are unlikely to occur spontaneously for many people and may not represent goals that are feasible for many adolescent alcohol-focused interventions.

Heavy-drinking friends can influence an individual's drinking in many ways (Borsari & Carey, 2001) and many interventions for adolescent alcohol use that have demonstrated clinical efficacy target network-related mechanisms, including reduced susceptibility to social influence, through both adolescent- and parent-based interventions (Borsari et al., 2007; Larimer & Cronce, 2007; Prestwich et al., 2016; Smit, Verdurmen, Monshouwer, &

Smit, 2008; Wood, Read, Mitchell, & Brand, 2004). Interventions that reduce social influence or social selection for networks as a whole (e.g., school- and community-based prevention programs; Foxcroft & Tsertsvadze, 2012) may reduce rates of heavy drinking and clustering based on similarity in drinking behavior within adolescent social networks. Individually-targeted interventions that reduce susceptibility to social influence may also reduce drinking, particularly they target adolescents who are more susceptible to social influence and social selection and who also have friends who drink heavily. Interventions that reduce susceptibility to social influence may work, in part, by disrupting the feedback loop created when social influence and social selection operate simultaneously, allowing one to more easily change their drinking behavior without requiring significant changes to their existing social environments.

The present study, as with all simulation studies, required several assumptions that limit its generalizability. Social ties were equally weighted even though real-world social ties may vary in importance and influence (e.g., Longabaugh et al., 1993). Changes in ties were memoryless (i.e., only influenced by present state of the system and not on previous states), even though real social ties are likely to be influenced by historical states. Many potentially important relationships were not modeled, including those involving individuals outside of the actors' schools; thus, the present study may not have included all of the most important actors in the simulated social networks. Several parameters that could influence friendships and drinking statuses also were not modeled (e.g., smoking statuses, demographic characteristics; Barnett et al., 2014; Huang et al., 2014), and it is possible that their omission could have produced simulated networks that differed from real-world adolescent networks in key ways, in turn affecting the clustering and intervention effects tested here. The underlying cognitive and behavioral mechanisms of social influence (e.g., biases in perceived drinking norms) also were not explicitly incorporated within the models. In other words, the simulation methods used here necessarily simplified many of the complexities of human social systems and behaviors, and the present results should therefore be interpreted for their theoretical value in testing of hypothetical interventions within dynamic social systems. Additionally, the reference sample of Southern California 10th graders may have limited generalizability to other populations that benefit from network-based interventions (e.g., adults in alcohol treatment; Litt et al., 2009; McCrady et al., 2009).

The present study also had several strengths. The methodology complements approaches that utilize real-world data by modeling processes that affect drinking and friendships. The use of simulations allowed the underlying parameters that guided network changes to be controllable, which is not always possible in the real world. The method also allowed many networks to be generated according to the same set of parameters (i.e., 500 trials in each combination of parameters) and allowed copies of the same networks to be subject to the different interventions to facilitate better comparison. Finally, the approach used here addresses an important gap in the literature by modeling how and for whom individual-focused alcohol interventions may work within the dynamic social contexts that they occur (Hunter-Reel et al., 2009; Leonard, 2015), which may help identify and refine hypotheses for future research.

Conclusion

The social environment can actively facilitate and maintain changes in alcohol use. Simulations of social networks provide a novel method for modeling alcohol use, social networks, and change over time within the context of dynamically-evolving social systems. Treatment approaches that reduce adolescents' susceptibility at an individual or population level may reduce alcohol use, particularly for adolescents with the heaviest-drinking friends. Additional research may aim to target adolescents who meet these criteria and further validate the differential conditions under which network-based interventions are most effective.

Acknowledgments

This work was supported by National Institute on Alcoholism and Alcohol Abuse of the National Institutes of Health, award numbers F31AA021031 and K01AA024796. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. Portions of this work have been presented at the annual meetings of the Research Society on Alcoholism, Association of Behavioral and Cognitive Therapies, and American Psychological Association.

References

Andrews JA, Tildesley E, Hops H, Li F. The influence of peers on young adult substance use. Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association. 2002; 21(4):349–357.

Bahr DB, Browning RC, Wyatt HR, Hill JO. Exploiting social networks to mitigate the obesity epidemic. Obesity. 2009; 17(4):723–728. DOI: 10.1038/oby.2008.615 [PubMed: 19148124]

Barnett NP, Ott MQ, Clark MA. The relevance of network prominence and reciprocity of relationships for alcohol use and alcohol-related problems in a college residence hall network. Psychology of Addictive Behaviors. 2014; 28(4):980–989. [PubMed: 25528047]

Borsari B, Carey KB. Peer influences on college drinking: A review of the research. Journal of Substance Abuse. 2001; 13(4):391–424. [PubMed: 11775073]

Borsari B, Murphy JG, Barnett NP. Predictors of alcohol use during the first year of college: Implications for prevention. Addictive Behaviors. 2007; 32:2062–2086. [PubMed: 17321059]

Bates D, Maechler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. Journal of Statistical Software. 2015; 67(1):1–48.

Braun RJ, Wilson RA, Pelesko JA, Buchanan JR, Gleeson JP. Applications of small-world network theory in alcohol epidemiology. Journal of Studies on Alcohol. 2006; 67(4):591–599. [PubMed: 16736079]

Cheadle JE, Walsemann KM, Goosby BJ. Teen alcohol use and social networks: The contributions of friend influence and friendship selection. Alcoholism & Drug Dependence. 2015; 3(5):1–9.

Chi FW, Kaskutas LA, Sterling S, Campbell CI, Weisner C. Twelve-step affiliation and 3-year substance use outcomes among adolescents: Social support and religious service attendance as potential mediators. Addiction. 2009; 104:927–939. [PubMed: 19344442]

Fairlie AM, Wood MD, Laird RD. Protective effect of parents on peer influences and college alcohol involvement. Psychology of Addictive Behaviors. 2012; 26(1):30–41. [PubMed: 21574670]

Fitzpatrick BG, Martinez J, Polidan E, Angelis E. On the effectiveness of social norms intervention in college drinking: The roles of identity verification and peer influence. Alcoholism: Clinical and Experimental Research. 2016; 40(1):141–151.

Foxcroft DR, Tsertsvadze A. Universal alcohol misuse prevention programmes for children and adolescents: Cochrane systematic reviews. Perspectives in Public Health. 2012; 132(3):128–134. [PubMed: 22700577]

Galea S, Hall C, Kaplan GA. Social epidemiology and complex system dynamic modelling as applied to health behaviour and drug use research. International Journal of Drug Policy. 2009; 20(3):209–216. http://doi.org/10.1016/j.drugpo.2008.08.005. [PubMed: 18930649]

Huang GC, Unger JB, Soto D, Fujimoto K, Pentz MA, Jordan-Marsh M, Valente TW. Peer influences: the impact of online and offline friendship networks on adolescent smoking and alcohol use. The Journal of Adolescent Health. 2014; 54(5):508–514. http://doi.org/10.1016/j.jadohealth.2013.07.001. [PubMed: 24012065]

Hunter-Reel D, McCrady BS, Hildebrandt T. Emphasizing interpersonal factors: An extension of the Witkiewitz and Marlatt relapse model. Addiction. 2009; 104:1281–1290. [PubMed: 19549057]

Kelman HC. Compliance, identification, and internalization: Three processes of attitude change. The Journal of Conflict Resolution. 1958; 2(1):51–60.

Larimer ME, Cronce JM. Identification, prevention, and treatment revisited: Individual-focused college drinking prevention strategies 1999–2006. Addictive Behaviors. 2007; 32:2439–2468. [PubMed: 17604915]

Latkin CA, Knowlton AR. Social network assessments and interventions for health behavior change: A critical review. Behavioral Medicine. 2015; 41(3):90–97. DOI: 10.1080/08964289.2015.1034645 [PubMed: 26332926]

Leonard KE. Perspective: Beyond the neural circuits. Nature. 2015; 522(7557):S56. http://doi.org/10.1038/522S56a. [PubMed: 26107097]

Leung RK, Toumbourou JW, Hemphill SA. The effect of peer influence and selection processes on adolescent alcohol use: a systematic review of longitudinal studies. Health Psychology Review. 2014; 8(4):426–457. http://doi.org/10.1080/17437199.2011.587961. [PubMed: 25211209]

Litt MD, Kadden RM, Kabela-Cormier E, Petry NM. Changing network support for drinking: Network Support Project 2-year follow-up. Journal of Consulting and Clinical Psychology. 2009; 77(2):229–242. DOI: 10.1037/a0015252 [PubMed: 19309183]

Longabaugh R, Beattie M, Noel N, Stout R. The effect of social investment on treatment outcome. Journal of Studies on Alcohol. 1993; 54(4):465–478. [PubMed: 8341050]

Mathys C, Burk WJ, Cillessen AHN. Popularity as a moderator of peer selection and socialization of adolescent alcohol, marijuana, and tobacco use. Journal of Research on Adolescence. 2013; 23(3):513–523. http://doi.org/10.1111/jora.12031.

McCrady BS, Epstein EE, Cook S, Hildebrandt T, Jensen N. A randomized trial of individual and couple behavioral alcohol treatment for women. Journal of Consulting and Clinical Psychology. 2009; 77(2):243–256. http://doi.org/10.1037/a0014686. [PubMed: 19309184]

Meisel MK, Kenny S, Barnett NP. Examination of social network composition, alcohol use and response to alcohol consequences among college students. Symposium presented at the annual meeting of the Research Society on Alcoholism, New Orleans, LA [Abstract]. Alcoholism: Clinical and Experimental Research. 2016; 40:259A.

Mercken L, Steglich C, Knibbe R, de Vries H. Dynamics of friendship networks and alcohol use in early and mid-adolescence. Journal of Studies on Alcohol and Drugs. 2012; 73:99–110. http://dx.doi.org/10.15288/jsad.2012.73.99. [PubMed: 22152667]

Mundt MP, Mercken L, Zakletskaia L. Peer selection and influence effects on adolescent alcohol use: A stochastic actor-based model. BMC Pediatrics. 2012; 12(115):1–10. [PubMed: 22208358]

Parra GR, Krull JL, Sher KJ, Jackson KM. Frequency of heavy drinking and perceived peer alcohol involvement: Comparison of influence and selection mechanisms from a developmental perspective. Addictive Behaviors. 2007; 32:2211–2225. http://dx.doi.org/10.1016/j.addbeh.2007.02.013. [PubMed: 17428616]

Prestwich A, Kellar I, Conner M, Lawton R, Gardner P, Turgut L. Does changing social influence engender changes in alcohol intake? A meta-analysis. Journal of Consulting and Clinical Psychology. 2016; 84(10):845–860. [PubMed: 27243967]

Ripley, R., Boitmanis, K., Snijders, TAB. RSiena: Siena – Simulation Investigation for Empirical Network Analysis, version 1.1-232. 2013. Computer software available at http://CRAN.R-project.org/package=RSiena

Sánchez E, Villanueva RJ, Santonja FJ, Rubio M. Predicting cocaine consumption in Spain: A mathematical modelling approach. Drugs: Education, Prevention, and Policy. 2011; 18(2):108–115. DOI: 10.3109/09687630903443299

Schaefer DR, Adams J, Haas SA. Social networks and smoking: exploring the effects of peer influence and smoker popularity through simulations. Health Education & Behavior: The Official Publication of the Society for Public Health Education. 2013; 40(1 Suppl):24S–32S. http://doi.org/10.1177/1090198113493091. [PubMed: 24084397]

Smit E, Verdurmen J, Monshouwer K, Smit F. Family interventions and their effect on adolescent alcohol use in general populations: A meta-analysis of randomized controlled trials. Drug and Alcohol Dependence. 2008; 97:195–206. [PubMed: 18485621]

Snijders TAB. Stochastic actor-oriented models for network change. Journal of Mathematical Sociology. 1996; 21(1–2):149–172.

Snijders TAB. The statistical evaluation of social network dynamics. Sociological Methodology. 2001; 31(1):361–395. DOI: 10.1111/0081-1750.00099

Snijders, TAB. NetworkSimulation.R: A script for simulation with RSiena. 2010. Computer code available online at https://www.stats.ox.ac.uk/~snijders/siena/NetworkSimulation.R

Snijders TAB, van de Bunt GG, Steglich CEG. Introduction to stochastic actor-based models for network dynamics. Social Networks. 2010; 32(1):44–60. DOI: 10.1016/j.socnet.2009.02.004

Tebb KP, Erenrich RK, Jasik CB, Berna MS, Lester JC, Ozer EM. Use of theory in computer-based interventions to reduce alcohol use among adolescents and young adults: A systematic review. BMC Public Health. 2016; 16(517):1–33. [PubMed: 26728978]

Turrisi R, Jaccard J, Taki R, Dunnam H, Grimes J. Examination of the short-term efficacy of a parent intervention to reduce college student drinking tendencies. Psychology of Addictive Behaviors: Special Issue on Understanding Binge Drinking. 2001; 15(4):366–372.

van der Vorst H, Engels RCME, Burk WJ. Do parents and best friends influence the normative increase in adolescents' alcohol use at home and outside the home? Journal of Studies on Alcohol and Drugs. 2010; 71(1):105–114. [PubMed: 20105420]

Verbrugge LM. The Structure of Adult Friendship Choices. Social Forces. 1977; 56(2):576–597. http://doi.org/10.2307/2577741.

Bertalanffy, LV. General System Theory: Foundations, Development, Applications. New York: George Braziller, Inc.; 1968.

Wang C, Hipp JR, Butts CT, Jose R, Lakon CM. Coevolution of adolescent friendship networks and smoking and drinking behaviors with consideration of parental influence. Psychology of Addictive Behaviors. 2016; 30(3):312–324. [PubMed: 26962975]

Wood MD, Fairlie AM, Borsari B, Capone C, Laforge R, Carmona-Barros R. Brief motivational and parent interventions for college studetns: A randomized factorial study. Journal of Consulting and Clinical Psychology. 2010; 78(3):349–361. [PubMed: 20515210]

Wood MD, Read JP, Mitchell RE, Brand NH. Do parents still matter? Parent and peer influences on alcohol involvement among recent high school graduates. Psychology of Addictive Behaviors. 2004; 18(1):19–30. [PubMed: 15008682]

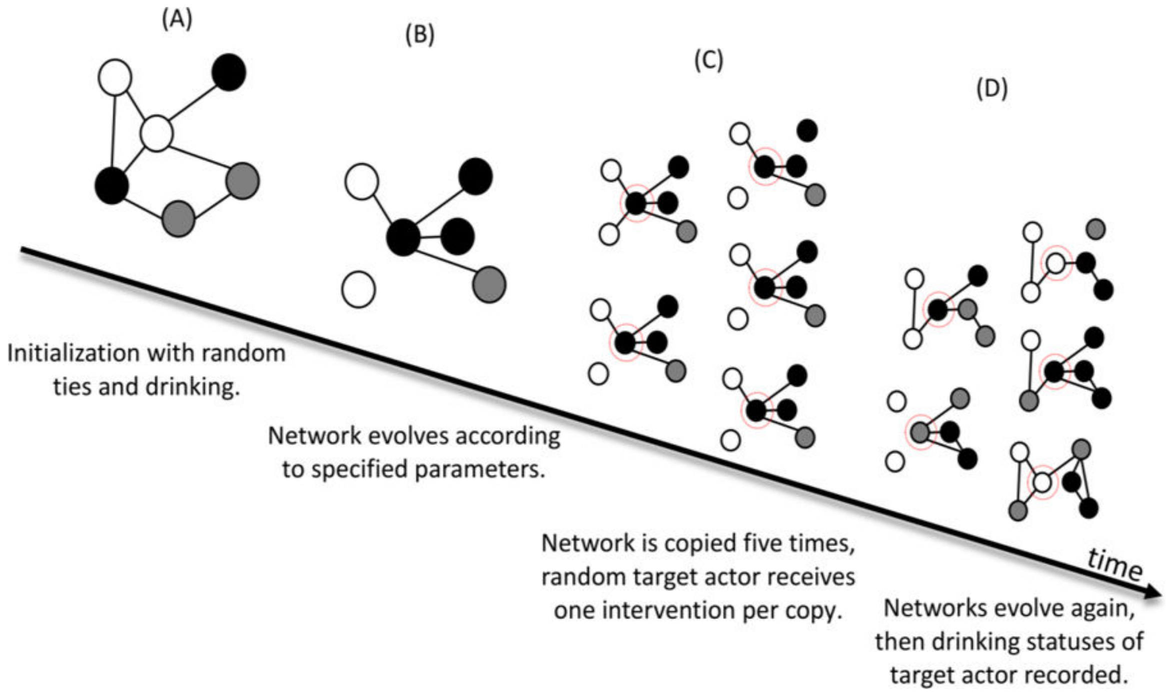

Figure 1.
Simulation procedures.
Networks are first generated with completely random ties and drinking statuses (A), then evolve according to the network and behavioral parameters specified in text (B). Five copies of each network are then produced and the same heavy-drinking network member is targeted for a different intervention in each network copy (C). The network then evolves again according to the same parameters in Table 1 and the drinking status of the target actor is recorded at the conclusion of the simulation (D). The process is then repeated for 500 trials per condition. Shades of nodes indicate actor drinking statuses, lines between nodes indicate social ties between actors, encircled node indicates heavy-drinking actor targeted for intervention. The simulated networks each included 287 actors; only 6 actors are shown here for illustration. Darker nodes indicate heavier drinkers; lines between nodes indicate social ties.

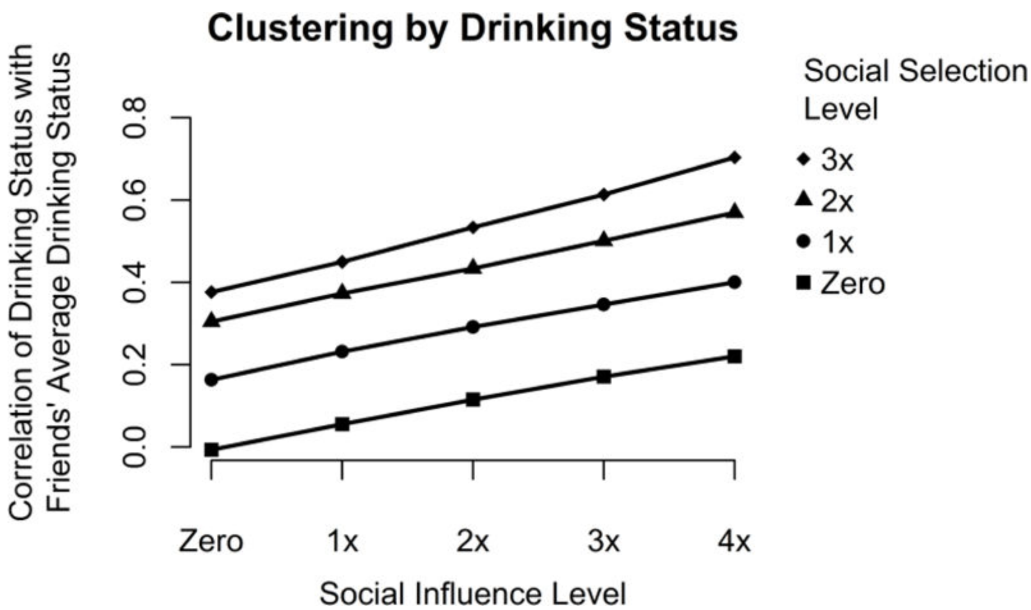

Figure 2.

Clustering by drinking status.

Clustering represented as mean Pearson correlations between drinking statuses and the mean drinking statuses of friends. See Table 1 for explanation of social influence and social selection values.

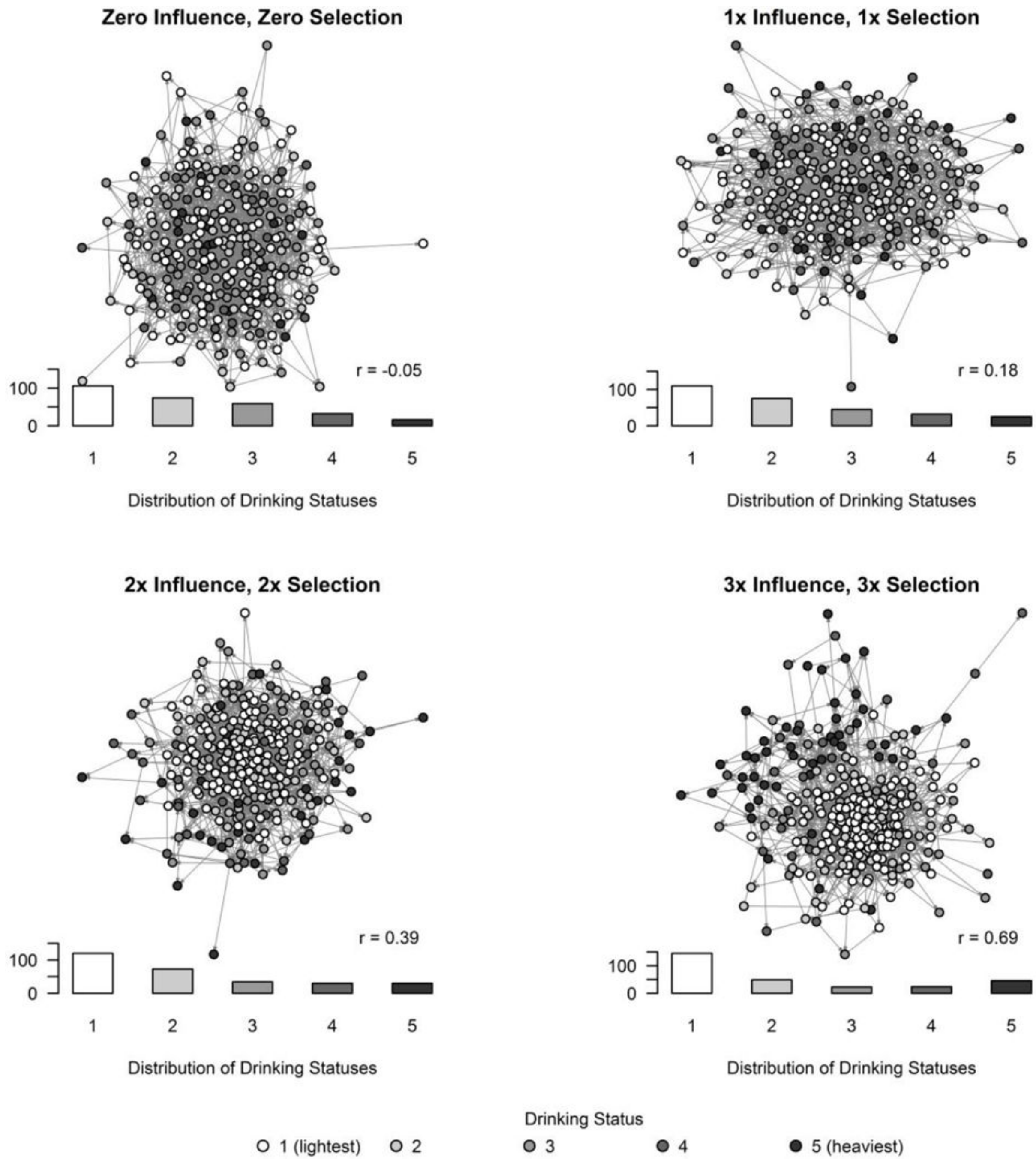

Figure 3.
Example network graphs and distributions of drinking statuses within networks.

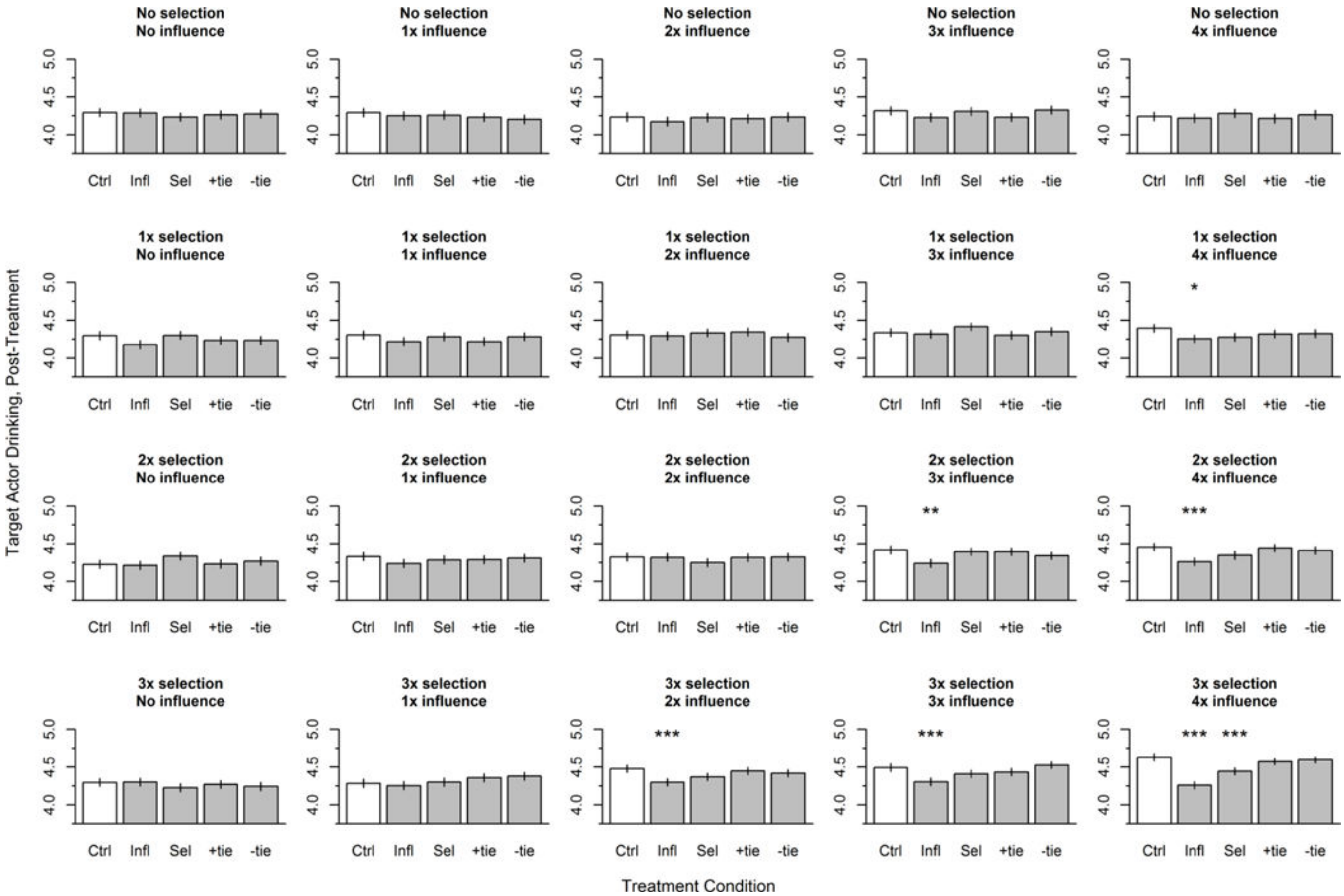

Figure 4.

Main effects of interventions on target actor drinking.

Bar graphs indicate the mean drinking status of actors targeted for intervention after completion of the simulation. Vertical lines indicate ± 1 standard error of the mean. Treatments that significantly differed from the control are indicated by asterisks. See Table 1 for explanation of social influence and social selection values. *p<.05, **p<.01, ***p<.001, all p-values are adjusted using Bonferroni correction. Ctrl=control condition, Infl=eliminating susceptibility to social influence, Sel=eliminating susceptibility to social selection, +tie=extending new tie to non-drinking actor, −tie=removing existing tie to heaviest drinking friend.

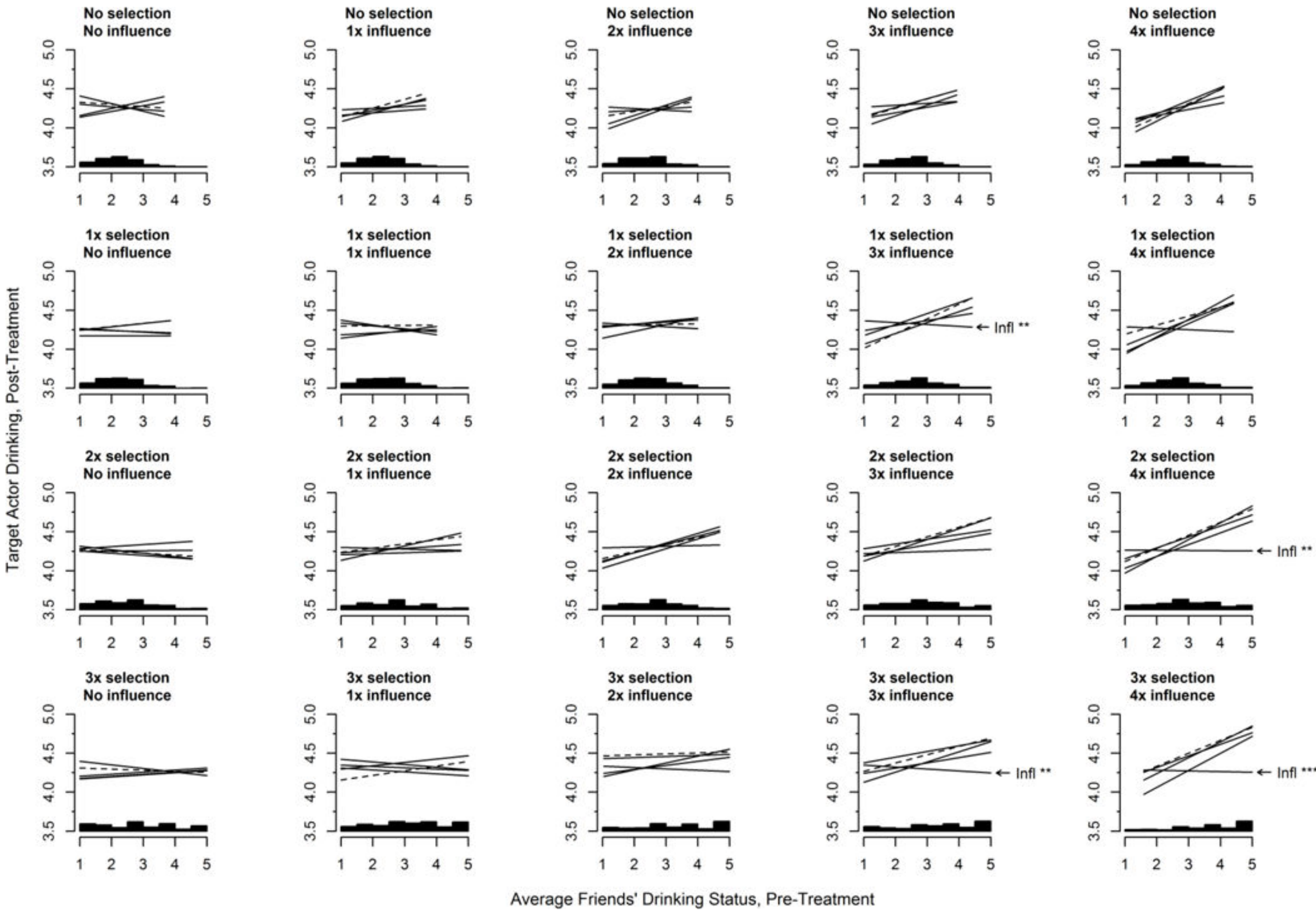

Figure 5.

Moderation of treatment effects by pre-treatment friends' drinking.

Diagonal lines indicate the associations between friends' average drinking status before treatment (x-axis) and post-treatment target actor drinking (y-axis) for each of the treatment conditions (separate lines). The control condition is indicated by a dashed line and only treatment conditions with significantly different slopes from the control condition are labeled to facilitate readability. Black histograms at the bottom of each plot indicate the distributions of friends' average drinking status before treatment. Infl = treatment condition that eliminated susceptibility to social influence. See Table 1 for explanation of social influence and social selection values. ***p*<.01, ****p*<.001, all *p*-values are adjusted using Bonferroni correction.

Table 1

Network Effect Values Used in Simulations

Network Effect	Social Selection Level: Zero	1x	2x	3x		Description of Effect
Outdegree	−2.41	−2.53	−2.73	−3.02		Controls number of friendships formed
Drinking Similarity	0	0.39	0.78	1.17		Tendency to form friendships based on similarity in drinking statuses
Transitivity	0.49	0.49	0.49	0.49		Tendency to form relationships with friends-of-friends
Reciprocity	1.85	1.85	1.85	1.85		Tendency to form friendships with others who extend ties to actor
Three-Cycle	−0.35	−0.35	−0.35	−0.35		Tendency for network closure
Friendship Rate	13.17	13.17	13.17	13.17		Typical number of opportunities to change friendships
Drinking Effect	Social Influence Level: Zero	1x	2x	3x	4x	Description
Linear Drinking	−0.32	−0.32	−0.32	−0.32	−0.32	Linear distribution of drinking
Quadratic Drinking	0.09	0.09	0.09	0.09	0.09	Quadratic distribution of drinking
Social Influence (average alter)	0	0.19	0.38	0.57	0.76	Tendency to change drinking status toward the average drinking status of friends
Drinking Rate	2.24	2.24	2.24	2.24	2.24	Typical number of opportunities to change drinking status

Note. Values at the “1×” levels are reference values from a meta-analysis provided by Huang et al. (2014). Levels of 2×, 3×, and 4× indicate the degree of increased size of social selection or social influence relative to these reference values. In the present study, all levels of social selection were crossed with all levels of social influence. Outdegrees were adjusted slightly from their original values of −2.66 at each level of social selection to provide approximately 5.17 outgoing ties per actor. Networks first evolved using friendship and drinking *rate* parameters that were 5 times larger than those shown in the table here to allow adequate evolution after they were initialized using completely random drinking and friendship values (per Snijders, 2010).