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Insight into Selecting Adolescents for Drinking Intervention Programs: A Simulation Based on Stochastic Actor-Oriented Models

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Abstract

Adolescent drinking remains a prominent public health and socioeconomic issue in the United States with costly consequences. While numerous drinking intervention programs have been developed, there is little guidance whether certain strategies of participant recruitment are more effective than others. The current study aims at addressing this gap in the literature using a computer simulation approach, a more cost-effective method than employing actual interventions. We first estimate Stochastic Actor-Oriented models for two schools from the National Longitudinal Study of Adolescent to Adult Health (Add Health). We then employ different strategies for selecting adolescents for the intervention (either based on their drinking levels or their positions in the school network) and simulate the estimated model forward in time to assess the aggregated level of drinking in the school at a later timepoint. The results suggest that selecting moderate or heavy drinkers for the intervention produces better results compared to selecting casual or light drinkers. The intervention results are improved further if network position information is taken into account, as selecting drinking adolescents with a higher in-degree or higher eigenvector centrality values for intervention yields the best results. Results from this study help elucidate participant selection criteria and targeted network intervention strategies for drinking intervention programs in the U.S.

Keywords: Drinking intervention programs; Peer networks; Computer simulation; Stochastic Actor-Oriented models

Introduction

Adolescent drinking results in more than 4,300 deaths along with 119,000 emergency room visits for alcohol-related injuries and other conditions each year, yielding $24 billion in economic cost (CDC 2020). Therefore, adolescent drinking remains a prominent public health and socioeconomic issue in the U.S. with extensive and costly consequences. While the overall prevalence of adolescents having ever drunk alcohol decreased from 81.6% to 60.4% between 1991 and 2017 in the United States, it has flattened from 2015 to 2017 (CDC 2017). Adolescent drinking is associated with multiple negative behavioral and health outcomes, including unplanned/unprotected sexual behavior (Hass et al. 2017), impaired academic performance (Balsa et al. 2011), physical violence (van Lier et al. 2009), homicide (Hohl et al. 2017), disruption in sleep habits (Valerio et al. 2016), suicide attempts (Schilling et al. 2009), use of other substances (Wang et al. 2016), and motor vehicle accidents and fatalities (NHTSA 2017).

For all these reasons, public health scholars have naturally been interested in designing and conducting interventions against adolescent drinking. However, a first challenge is that conducting such interventions is both time and economically costly. Given the uncertainty about the possible efficacy of an intervention before it is conducted, along with the limited success achieved by some interventions, there is a clear need to design simulations based on prior empirical evidence that might provide insights into which intervention strategies might have the most possibility of success before they go into the field. A second challenge is that they live in dense peer and familial networks that can impact the strategies of the intervention. Thus, prior evidence on how adolescents might respond to particular interventions conducted within an experimental laboratory setting cannot take into account how an adolescent's social networks might impact the delivery of the intervention message. Again, using insights from existing empirical studies of adolescent networks and how they impact influence and selection effects of substance use behavior might be informative if then employed within a simulation framework. Our goal herein is to provide such simulation evidence in the hope that it will be useful to practitioners who wish to conduct interventions within adolescent school networks.

Prior Drinking Interventions

In this section we broadly survey drinking intervention programs conducted by public health and social scientists. Although our study will focus on simulating drinking interventions among high school students, we include in our review interventions conducted on younger (junior high school) and older (college) students as well. We acknowledge that some of these processes may operate differently on these other populations, a point to which we will return in the discussion.

The National Institutes of Health (NIH) initiated the "Just Say No" campaign during the 1980s, which was supported by First Lady Nancy Reagan during her husband's presidency and developed into an anti-drug movement. However, the U.S. Government Accountability Office reported that this campaign was not effective in reducing adolescent drinking (GAO 2006). The Drug Abuse Resistance Education (DARE) program begun from Los Angeles in 1983 focused on providing to youth information about risks and consequences of drinking (BJA 1991), but again there was little evidence supporting the proposition that information and knowledge alone could reduce drinking behavior among adolescents (Larimer and Cronce 2002, 2007).

The idea of skill training is advanced to resist peer pressure on drinking among junior high school students in Project SMART (Hansen et al. 1988) and Midwestern Prevention Project (Pentz et al., 1989). The underlying theory is that adolescent drinking could be influenced by personal (demographic, biological, dispositional, sociocultural), interpersonal (peer influence), and environmental (family, neighborhood, school) factors (Botvin 1996; Dimeff et al. 1998).

The Alcohol Skills Training Program (ASTP) targeted enhancing the effectiveness of coping responses, building and bolstering skills, and increasing self-efficacy in order to change college students' drinking behavior and associated lifestyle habits (Baer et al. 1992). The Life Skills Training (LST) program attempted to integrate education with ASTP – on the one hand, youths are provided factual information about the adverse effects of alcohol use, alcohol pharmacology, and the alternatives to alcohol use; on the other hand, personal and social skills training as well as social-resistance skills training were offered to participants (Botvin 1996).

The Brief Alcohol Strategies and Intervention for College Students (BASICS) builds on the ATSP (Dimeff et al. 1998). It includes brief motivational interventions (BMI) that create the will for changes among drinking adolescents, while skills training from ATSP provides the way. Additional personalized normative feedback (PNF) summarizes each youth's drinking habits, a comparison of drinking habits to general norms, risk factors (e.g., family history, degree of alcohol dependence), results of medical or psychological assessment (e.g., liver function, neuropsychological or cognitive impairment from heavy drinking), and cognitive factors (e.g., beliefs about the common effects from drinking). The BASICS program is considered to be the most effective drinking invention program so far and has many variants. For example, the Risk Skills Training Program (RSTP) combines education with skills training from BASICS (D'Amico and Fromme 2000). BASICS has been used along with resetting peer-oriented norms on drinking (Larimer et al. 2001; Carey et al. 2006). In more recent years, the BASICS is applied on mobile phones (e.g., BASICS curriculum adapted to be a mobile intervention: BASICS-Mobile, see Witkiewitz et al. 2014; Text Message Alcohol Program: TMAP, see Bock et al. 2016; BASICS-Mobile + TMAP, see Merrill et al. 2018), a computer-based online platform (e.g., Doumas and Esp 2019), and smartphones (e.g., Bertholet et al. 2020).

Most drinking prevention programs adopt a classic experimental design: at the first time point (t_1) the participants take a pre-test of their drinking levels and are randomly assigned to an experimental group and a control group; then at the second time point (t_2), participants in the experimental group receive the drinking intervention while those in the control group do not; and finally at the third time point (t_3), participants in both groups take a post-test of their drinking levels, which are compared across time and groups for effect assessment (Hansen et al. 1988; Pentz et al., 1989; Baer et al. 1992; Botvin 1996; Darkes and Goldman 1998; Walters et al. 2000, 2007; Musher-Eizenman and Kulick 2003; Carey et al. 2006; Neighbors et al. 2011; Witkiewitz et al. 2014; Bock et al. 2016; Merrill et al. 2018; Doumas and Esp 2019).

One question that these programs face is which students should be targeted in an intervention, or, relatedly, which students to target first. For example, a common strategy is to pick heavy drinkers (or problem drinkers, binge drinkers, and alcoholics) for intervention among college students (Dimeff et al. 1998; Carey et al. 2006; Walters et al. 2007; Witkiewitz et al. 2014; Bock et al. 2016; Merrill et al. 2018). A few studies on college-aged adolescents instead chose to intervene on both moderate and heavy drinkers (Walters et al. 2000; Musher-Eizenman and Kulick 2003), and one case selected all drinkers – heavy, moderate, and light (Jones et al. 1995). Other interventions have instead selected just moderate drinkers (Darkes and Goldman 1998), whereas another selected non-drinkers and light drinkers (Neighbors et al. 2011). However, we lack systematic evidence of which strategy is more successful, and to our knowledge no previous research has investigated whether the efficacy of using the same intervention technique gives different or similar results when targeting drinkers at different levels. Therefore, despite the long history of drinking intervention programs, the theoretical and methodological foundations of participant recruitment remain assumptive and preliminary.

Moreover, since peers have a significant impact on adolescent drinking for high school and college students (Botvin, 1996; Dimeff et al. 1998; Larimer et al. 2001; Carey et al. 2006), "network interventions" (Valente 2012), i.e., intervention programs that account for and operate via peer networks, are expected to be more effective than their non-network counterparts. Their typical strategy is to identify participants who are influential based on certain network properties (e.g., degree centrality, closeness centrality, between centrality, and eigenvector centrality in Valente 2012) and target them for the drinking intervention. The presumption is that their salient network positions will better enable them to transmit the intervention effect to others they connect with. A few studies have examined the effect of network interventions on substance use behaviors among high-risk adolescents (Valente et al. 2007) and on alcohol, drug, and HIV risk behaviors among individuals transitioning from homelessness to housing (Kennedy et al. 2016).

The question then is which network position would be most important for deciding who to target in interventions. Some research has posited that it is simply the presence of many social ties in the network that matters: in the case of out-degree this would imply that the adolescent has many connections to others in the school, whereas larger in-degree might indicate that the student is relatively popular (Valente 2012). Valente and colleagues have posited that adolescents in a bridging position in the network – that is, those tend to link together different subgroups – will be most important for norm transmission and therefore are the optimal adolescents to target in an intervention (Valente and Fujimoto 2010; Everett and Valente 2016). Yet another possibility is that those in highly cohesive subgroups are important as these groups might be able to maintain such altered norms, and therefore small group cohesiveness is the focus (Berten and Rossem 2011). In the simulation study we explore these different possibilities.

This review of the literature raises several key points. First, our goal here is not to explain which intervention strategies might be best to change an adolescent's drinking behavior. Instead, we take for granted that some such techniques exist, and instead ask how this change in drinking behavior might be subsequently enhanced even for the most effective individual-level intervention. Since interventions are costly to implement, we argue that it is useful to provide simulation evidence of which intervention techniques are more likely to be successful long-term within a social network. Specifically, we ask whether it is better to select heavy drinkers rather than moderate or light drinkers for the intervention. We also ask whether it is better to consider adolescents' positions in the social network when selecting whom to intervene with, and which network position most enhances the long-term success of the treatment.

The current study aims at addressing these two research questions with simulations using the Stochastic Actor-Oriented (SOA) modelling strategy (Snijders et al. 2010; Steglich et al. 2010), which provides a data-generating tool under various simulating scenarios. As in prior simulation studies (Schaefer et al. 2013; Lakon et al. 2015; Wang et al. 2017, 2018), we first build SOA models from real-world data that describe the relationships between adolescent drinking behavior and their peer networks. In contrast to prior simulation studies, the current study mimics intervention strategies by implementing varying participant selection strategies and then forward simulating the network and behavior. We therefore select adolescents in the network at t_1 based on various behavioral and network criteria to mimic a typical intervention strategy, change the drinking level of selected participants to non-drinkers at t_2 to mimic a successful drinking intervention program, and then simulate forward the network and behavior to t_3 to assess the consequences of the intervention based on adolescent drinking levels in the school. In the next section we discuss how this simulation approach will work, introduce the data and measures, the SOA modeling strategy, and the simulation strategies.

Methods

Data

The current study construct samples from two large schools during early waves of the National Longitudinal Study of Adolescent to Adult Health (Add Health; Harris et al. 2019). "Jefferson High" (Bearman et al. 2004) is a rural Midwest public high school (n = 1,024) and "Sunshine High" (Shoham et al. 2012) is a suburban Northeast public high school (n = 2,104). Add Health administrated an in-school survey in 1994 (t_1) and two follow-up surveys at students' homes in 1995 (t_2) and 1996 (t_3) for all attending students in these two schools.

Measures

The students were asked "During the past twelve months, how often did you drink beer, wine, or liquor?" at t_1 and "During the past 30 days, on how many days did you drink alcohol?" at t_2 and t_3. We recategorize five response groups based on their alcohol use over the previous 12 months, i.e., non-drinkers (0 = "never"), casual drinkers (1 = "1-2 days"), light drinkers (2 = "once a month or less / 3-12 times in the past 12 months"), moderate drinkers (3 = "2 or 3 days a month"), and heavy drinkers (4 = "more than 1 or 2 days a week"). The peer network variable is based on questions asking the students to list up to five female and five male friends in each school. Covariates are introduced in the supplemental materials.

Model estimation method

The Stochastic Actor-Oriented (SOA) modelling strategy (Snijders et al. 2010; Steglich et al. 2010) interprets the adolescent drinking behavior and peer networks observed at discrete time points as a cumulative result of an underlying continuous time Markov-chain process. It first estimates the rate function λ_i which indicates the expected chance for an adolescent i to change his or her drinking behavior level and peer network ties between two consecutive time points. It then estimates how changes occur based on the actor's current drinking behavior and peer network configurations, referred to as objective function f_i, which is specified as a logistical choice model $\sum_k \beta_k s_{ik}(x)$, where β_k is the estimated parameter for the *k*th actor-specific effect $s_{ik}(x)$ and *x* is the feature of joint behavior/network state. The adolescent will compare the values on the objective function before and after making a change and seek to maximize the utility by disproportionately moving in the direction with higher benefit. The SOA modeling strategy has been used widely in the literature on adolescent drinking and peer networks (Mundt et al. 2012; Mathys et al. 2013; Osgood et al. 2013; Wang et al. 2015, 2016, 2018).

Simulation strategy

Based on the SOA models estimated from Jefferson High and Sunshine High, we conduct a series of simulations. *Plan 1.* We randomly select 10%, 20%, and 30% heavy drinkers (with a value of 4) at t_1, change their drinking levels to 0 at t_2 to mimic the success of the intervention, and then simulate their drinking behavior and peer networks forward in time to t_3. This is analogous to interventions that select individuals without regard to their network positions, and only in regard to being heavy drinkers. In Jefferson High 201 (or 19.7%) of the 1024 students are heavy drinkers, and thus we select 20, 40, and 60 for the 10%, 20%, and 30% interventions, respectively. In Sunshine High 299 (or 14.2%) of the 2104 students are heavy drinkers, and thus we select 30, 60, and 90 students for the 10%, 20%, and 30% interventions, respectively. We selected these same numbers of students for all the subsequent interventions we describe.

Plan 2. We alter plan 1 by selecting 10%, 20%, and 30% heavy drinkers at t_1 who had the highest values on each of the nine network properties listed in Table 1, change their drinking levels to 0 at t_2, and the simulated distributions of drinking levels at t_3 are compared with that from plan 1. These nine network properties reflect how influential each adolescent was in his or her peer networks from various perspectives. It may be that the number of social ties is important for an adolescent's influence, and we therefore account for this with measures of out-degree or in-degree. Given that being central in the network may be important, we include three different centrality measures (closeness, betweenness, and eigenvector). To account for the possible importance of cohesion in small groups, we construct a measure of the local clustering coefficient. The degree of linkage to the broader school network may be important, and we capture this with the *k*-core measure. Finally, persons in bridging positions may be important since they can link various smaller groups together, and thus we include two bridging measures introduced by Valente and colleagues (Valente and Fujimoto 2010; Everett and Valente 2016).

Plan 2a. The one condition from plan 1 and the nine conditions from plan 2 are replicated but instead of selecting heavy drinkers, we sequentially select casual drinkers (with a value of 1), or light drinkers (with a value of 2), or moderate drinkers (with a value of 3) at t_1, and the network and behavior are simulated forward in time. We then compare the levels of drinking in the schools at t_3 based on these simulations with those from plans 1 and 2.

Plan 2b. We alter plan 2 by selecting adolescents who had the highest values on each of the nine network properties listed in Table 1 and were drinkers at any level (i.e., with values from 1 to 4) for the intervention. The simulated distributions of drinking levels at t_3 are then compared with those from plans 1 and 2. Note that in plan 2 the level of drinking for an adolescent is the primary consideration and network properties are secondary when selecting adolescents for the intervention, whereas in plan 2b this prioritization is reversed.

<<<Table 1 about here>>>

Results

Descriptive statistics

Table 2 shows that the proportions of non-drinkers (with a value of 0) keep increasing and those of casual drinkers (with a value of 1) keep decreasing across the three time points in both schools; and the proportions of light, moderate, and heavy drinkers (with values from 2 to 4) fluctuate over time. Alcohol use is greater in Jefferson High than in Sunshine High. Regarding the friendship ties, the reciprocity index indicates out of all friendship ties how many of them are mutual, and is somewhat higher in Jefferson High (.34) compared to Sunshine High (.25). Table 2 also shows the means and standard deviations of nine network properties measured at t_1. These nine network properties will be used to select students for drinking intervention simulation. The descriptive statistics of covariates are shown in Table 1a of the supplemental materials.

<<<Table 2 about here>>>

Estimated Stochastic Actor-Oriented (SOA) Models

The details of the estimated SOA models are provided in Table 2a of the supplemental materials. The models reproduce the network structure and the distribution of drinking at t_3 well (Wang et al. 2015). To assess this, the *p*-value from the Monte Carlo test of Mahalanobis Distance statistics (Wang et al. 2020) is greater than .05, suggesting that the observed behavior distribution is not especially extreme compared to what would be expected from the estimated model. One primary result is a peer influence effect, as students in both schools tend to adopt the drinking levels of their friends. A second primary result is that students tend to select as friends those who have similar levels of drinking as themselves. Furthermore, in Jefferson High the positive drinking alter parameter indicates that heavy drinkers are more likely to be nominated as friends, indicating a popularity effect, that may be important in our simulation. These results, including the influence and selection effects, parallel those found in numerous studies (Mundt et al. 2012; Mathys et al. 2013; Osgood et al. 2013; Wang et al. 2015, 2016, 2018).

Simulation results

Simulation plan 1. We now turn to our simulation results. The first bar in Fig. 1 shows that with no intervention there are 34% non-drinkers at t_3 in Jefferson High. The remaining bars in this figure show the percentages of non-drinkers based on different selection strategies. For example, the second bar indicates that when 20% heavy drinkers are randomly selected for intervention there are 35.5% non-drinkers at t_3. This is an improvement over the 34% that exist without an intervention, although one might argue that it is not a very large improvement. For example, if one were successful in converting those 40 (or 20%) heavy drinkers at t_1 to be non-drinkers, this implies a 4% (i.e. 40 out of 1024) increase in non-drinkers in this school; however, here we see just a 1.5% gap between the percent existing based on no intervention versus that based on this random intervention. The difference is due to the "drag" of social network effects, which can impact drinking behavior even for those who became non-drinkers by t_2.

<<<Fig. 1 about here>>>

Simulation plan 2. The remaining bars in Fig. 1 show the results when selecting adolescents for the intervention based on various social network positions. The third and fourth bars (20peroutd and 20perind) select adolescents based on high out-degree or in-degree values, respectively. Although there is no improvement when selecting based on out-degree, the percent of non-drinkers rises to 36.1% at t_3 when selecting based on in-degree (a proxy for popularity of students). The next three bars show results when selecting adolescents for the intervention based on different centrality measures (closeness, betweenness, and eigenvector). The first two do no better than the random intervention strategy; however, selecting based on eigenvector centrality shows an improvement and does just as well as selecting based on in-degree and yields 36.1% non-drinkers. The remaining four strategies do not do as well and selecting based on local clustering coefficient (20perlcc) is the worst strategy (even worse than the random strategy).

Thus, selecting based on in-degree or eigenvector centrality have the best results in Jefferson High, and we find this whether selecting 10%, 20%, or 30% heavy drinkers for intervention (the results for 10% and 30% selection are shown in Figures 1a and 2a in supplemental materials).

The simulation results for Sunshine High are present in Fig. 2. The first bar in this figure shows that the model without an intervention implies 50.1% non-drinkers, and the various intervention strategies at best improve this 1.1% by t_3.[1] The improvement is 0.6% (to 50.7%) when randomly selecting 60 (or 20%) heavy drinkers for intervention. The results can be improved by selecting intervention targets based on certain network positions. We see that two of the best strategies are selecting adolescents for the intervention who have either high in-degree betweenness (51.2% non-drinkers at t_3) or high eigenvector centrality (51.1%). However, a few other network measures are almost equally effective: selecting based on high out-degree (51.1%), or high *k*-core (51.1%). In Sunshine High, selecting adolescents for intervention based on in-degree or eigenvector centrality produces the highest proportion of non-drinkers at t_3 when selecting 10% heavy drinkers for intervention, and those based on betweenness centrality or eigenvector centrality produce the highest proportion of non-drinkers at t_3 when selecting 30% heavy drinkers for intervention, as shown in Figures 3a and 4a of the supplemental materials.

<<<Fig. 2 about here>>>

Simulation plan 2a. We modify simulation plan 2 by selecting the same number of casual drinkers, light drinkers, or moderate drinkers rather than heavy drinkers for intervention. In Jefferson High, there is strong evidence that selecting casual drinkers rather than heavy drinkers for intervention has much worse results. Whereas we saw that there are 36.1% non-

[1] Thus, in Jefferson High the best intervention strategy increased the percentage of non-drinkers 1.5% compared to the number selected for the intervention that would have implied a 4% increase; this is 37.5% of the potential improvement (1.5/4). In Sunshine High, the ratio is 1.1% of 2.9%, which is 37.9%. So the ratios of the potential improvement is almost identical across the two schools.

drinkers at t_3 when selecting heavy drinkers with high in-degree or eigenvector centrality, when selecting casual drinkers the value is 34.9% (see Figure 5a in supplemental material). However, if we select light drinkers instead of heavy drinkers, the simulation results are nearly as effective, there are 35.9% non-drinkers at t_3 when selecting based on these two network positions (see Figure 6a in supplemental material). And the simulation results are equally effective if we select moderate drinkers instead of heavy drinkers (see Figure 7a in supplemental material).

Simulation plan 2b. Whereas in plan 2 we focus on the adolescents' drinking levels for selection into intervention and then prioritize based on values of the network measures, in plan 2b we instead prioritize the network measures and select for intervention those with the highest values on the particular network measure with the only proviso being that they engage in drinking at any level. This strategy yields results nearly as good as the earlier strategy focused on selecting 20% heavy drinkers who have relatively high values on the network measures (see Figure 8a in supplemental material). The best results are obtained when selecting adolescents for intervention based on in-degree (36% non-drinkers at t_3) or eigenvector centrality (35.9%). When we selected 30% for intervention, in-degree (36.7%) and eigenvector centrality (36.6%) were again the most effective strategies for selection, as they were when selecting 10% for intervention (35.0% and 35.2%), as shown in Figures 9a and 10a in supplemental material.

A less stringent assessment of intervention "success". In the prior analyses, we defined "success" for the intervention when adolescents remain non-drinkers at t_3. This is a strong criterion for success, so we also relax this and assess the results when defining success in cases when adolescents are either non-drinkers or only drink once or twice per year (the two lowest categories of drinking measure). The pattern of results based on this criterion was very similar to those already described for both schools. In Jefferson High, in-degree and Eigenvector centrality remained the two most effective selection strategies; whereas these two strategies earlier showed a 2.1% improvement over no intervention under the more stringent criterion, here they exhibit 3% and 2.9% improvements, respectively (Figure 11a in supplemental material). And if we relax the criterion even further and define success as when adolescents drink once a month or less (the three lowest categories of drinking measure), in-degree and Eigenvector centrality are the best strategies with 2.8% and 2.7% improvements, respectively, over no intervention (Figure 12a in supplemental material). The relative ranking of the remaining selection strategies in these two other definitions of intervention success remained the same as in our main analyses.

Discussion

The current study used a simulation strategy to model how drinking intervention programs might play out based on various participant selection strategies. Even when an intervention is successful in the short-term, it still is the case that the adolescents are in dense social networks that can impact their future behavior. We assessed the impact of these networks on the longer-term success (one year) of various intervention selection strategies. Thus, our interest here was in how iatrogenic effects might occur in the long-term consequences of an intervention strategy due to the effect of the school network; such iatrogenic effects are an important concern and have been highlighted in earlier intervention research (Dishion et al. 2001). Our simulation results showed that selecting light or casual drinkers for the intervention generally were less effective strategies. Instead, selecting heavy or moderate drinkers yielded the largest percentage of non-drinkers at t_3 across the simulations. Therefore, selecting moderate drinkers (Darkes and Goldman 1998) or both moderate and heavy drinkers (Walters et al. 2000; Musher-Eizenman and Kulick 2003) appears to be an optimal choice for drinking intervention programs based on this simulated scenario in a school with relatively high substance use levels.

Moreover, our findings corroborate Valente (2012) that network interventions generally outperform their non-network alternatives. While the nine network properties included in the current study reflect to what extent an adolescent is influential in his or her peer networks from different perspectives, the two most effective selection strategies in most cases were selecting adolescents for intervention based on high in-degree or eigenvector centrality. Adolescents with higher eigenvector centrality values do not necessarily have a large number of friends, but rather they tend to connect to other influential adolescents in their peer networks. When public health and social scientists are able to measure both drinking levels and network properties at the first stage of intervention programs, selecting those having higher eigenvector centrality values may more easily reset the peer norms on alcohol use and more efficiently diffuse the intervention effect to those they are connected but not in the intervention programs. Even easier is to select adolescents based on high in-degree, which also appeared to be a successful strategy across many of these simulations. This high in-degree might indicate that these are popular adolescents in the school network, and therefore have more ability to influence others to stop drinking.

Finally, we did not find different simulation results whether the intervention was primarily based on the drinking behavior of adolescents with the network position only of secondary importance, or the reversed criteria. When public health and social scientists have both behavior and network information at hand, it does not appear that prioritizing for selection into the intervention makes much difference between the two, highlighting the interdependence of behavior and network evolution processes.

The findings presented in the current study should be considered in light of the following limitations. First, our simulations are based on Add Health data collected from high school students in the mid-1990s, and high school/adolescent alcohol prevention can be different from college alcohol prevention. Although our simulation results logically make sense and match what are actually observed, future research needs to empirically verify their generalizability and we expect our findings to be confirmed or refined by public health practitioners conducting alcohol intervention programs among both high school and college student populations. Second, for simplicity our computer simulations change the drinking levels of all selected adolescents to 0 at t_2, but no drinking intervention programs in the real world are so effective. However, we would presume that in accounting for this just the proportion of successes in the network would change at t_3 for all strategies, and we have no reason to expect that such limited success would impact the ranking of the strategies. We leave this exploration for future work.

Despite these limitations, the current study has both methodological and practical implications. First, it illustrates the feasibility and merit of using simulation for school-based intervention research. Some prior studies have tuned up or down the parameters of certain key mechanisms (e.g., peer influence) (Schaefer et al. 2013; Lakon et al. 2015; Wang et al. 2017, 2018) to assess how such mechanisms might impact substance use behavior at the population level. Such a strategy provides insight into the impact of certain mechanisms on intervention strategies, as well as insight into how some processes might operate across a broader array of potential contexts. In the current study we adopted a strategy that mimicked intervention studies by changing the composition of substance users and non-users to see how this effect can be sustained over time. Yet another strategy would be to mimic intervention studies that intervene within the adolescents' homes – e.g., changing norms at home, or the availability of alcohol – as yet another way to assess the long-term consequents of such an intervention when it meets the peer networks of adolescents that can influence them to change their behavior. In short, we believe using such simulation would be an incredibly beneficial strategy for the prevention science field, as it has the potential to inform intervention development, assess iatrogenic effects in vitro, and provide a cost-effective strategy to do so. The ultimate goal of all such simulation strategies is to identify individuals who are more likely to move from a high-risk state to a low-risk state so an intervention program can attain its maximal benefit. With a sufficient number of adequately accurate models on tap, prevention scientists one day will be able to test the implications of prosocial changes by computer simulation before applying them in real life.

Second, this study provides guidelines for public health and social scientists to select participants for regular interventions (moderate drinkers or both moderate and heavy drinkers) and network interventions (adolescents having higher in-degree or eigenvector centrality values). And the latter will help address and modify the norms favoring drinking behavior through adolescent peer networks. We hope the current study helps elucidate more preferable participant selection criteria and further refines drinking intervention programs in the U.S.

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Conflict of interest The author declares that they have no conflict of interest.

Ethical approval The Add Health project was approved by the Institutional Review Board at the University of North Carolina, School of Public Health. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Written informed consent was given by the Add Health participants (or next of kin/caregiver) for their answers to be used in secondary data analysis.

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Table 1 Network properties for selecting participants

Network property	Note
Out-degree	Number of friend(s) a focal adolescent nominated. Adolescents with higher out-degree values are more active in the peer network.
In-degree	Number of other adolescents who nominated a focal adolescent as a friend. Adolescent with higher in-degree values are more popular in the peer network.
Closeness centrality	The inverse of the sum of the shortest distances from a focal adolescent to all the other adolescents. Adolescent with higher closeness centrality values can quickly interact with other adolescents in the peer network.
Betweenness centrality	The sum of proportions that a focal adolescent is on the short path(s) between any pair of other adolescents over all shortest path(s) between this pair of adolescents. Adolescents with higher betweenness centrality values have more control over the interaction paths in the peer network.
Eigenvector centrality	The principle eigenvector of a network adjacency matrix. Adolescents with higher eigenvector centrality values have friends also with higher eigenvector centrality values, but don't have necessarily have many friends.
Local clustering coefficient	The proportion of existing friendship tie(s) out of all possible friendship ties among a focal adolescent's friends. Adolescents with higher local clustering coefficient values are located in a tightly connected immediate neighborhood in the peer network.
k-core	A focal adolescent has *k* friends, who also have at least *k* friends. Adolescents with higher *k*-core values are more central in the peer network.
Valente-Fujimoto version (2010) bridge measure	The ratio of sum of changes in the peer network cohesion after removing a focal adolescent's each friendship tie over the number of the focal adolescent's all friendship ties. Adolescents with higher bridge values are more likely to disconnect the peer network if they are removed.
Everett-Valente version (2016) bridge measure	The ratio of the sum of a focal adolescent's doubled betweenness centrality value and the number of other adolescents in the peer network over the number of the focal adolescent's all friendship ties. Adolescents with higher bridge values are more likely to disconnect the peer network if they are removed.

Table 2 Descriptive statistics of dependent behavior and network variables

	Jefferson High (n = 1,024)			Sunshine High (n = 2,104)		
Drinking behavior (past 12 months, %)	t_1	t_2	t_3	t_1	t_2	t_3
0 = never	30.53	34.32	37.60	44.03	51.56	53.76
1 = 1 or 2 days	23.46	19.77	13.73	26.54	19.19	14.83
2 = once a month or less (3-12 times in the past 12 months)	12.70	18.55	15.98	8.59	12.35	11.11
3 = 2 or 3 days a month	13.63	14.34	14.04	6.66	6.06	6.80
4 = more than 1 or 2 days a week	19.67	13.01	18.65	14.19	10.84	13.50
Friendship networks						
Out-going ties	6,063	3,713	2,484	5,685	4,201	2,296
Reciprocity index	0.34	0.35	0.35	0.30	0.28	0.25
Transitivity index	0.18	0.19	0.20	0.19	0.19	0.14
Jaccard index		0.22	0.21		0.16	0.16
Limited nominations (%)	0	4.82	0.41	0	3.49	1.52
Out-degree, mean (SD)	6.21(3.36)			2.61(3.08)		
In-degree, mean (SD)	6.21(4.79)			2.61(2.55)		
Closeness centrality, mean (SD)	0.29(0.03)			0.00(0.00)		
Betweenness centrality, mean (SD)	2237.96(2296.38)			6537.50(9807.08)		
Eigenvector centrality, mean (SD)	0.02(0.02)			0.01(0.02)		
Local clustering coefficient, mean (SD)	0.22(0.16)			0.23(0.25)		
k-core value, mean (SD)	11.57(4.07)			5.17(3.21)		
Valente-Fujimoto version (2010) bridge measure, mean (SD)	0.00(0.00)			0.00(0.00)		
Everett-Valente version (2016) bridge measure, mean (SD)	289.21(151.27)			1267.40(1128.26)		

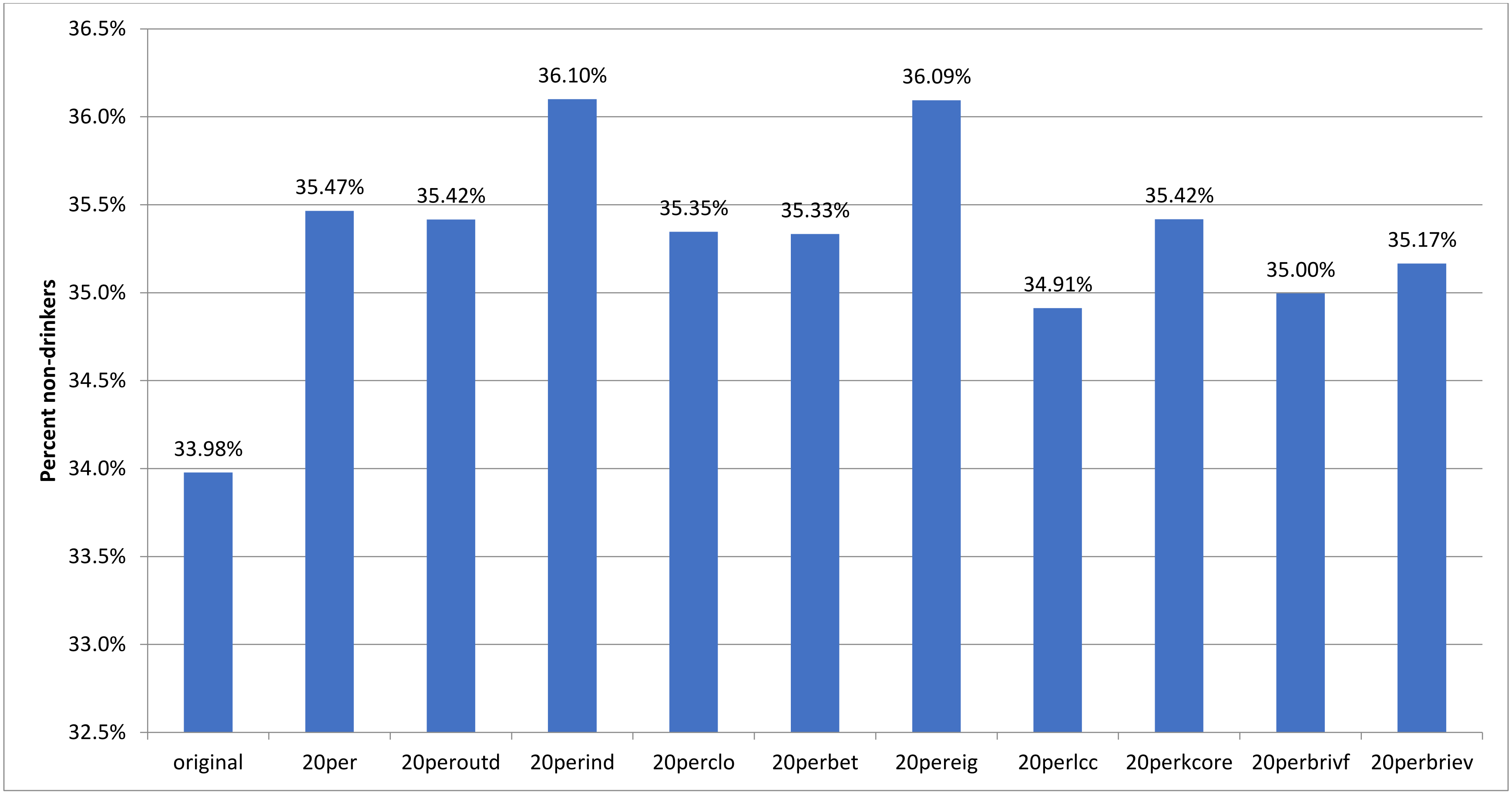

Fig. 1 The simulation results for non-drinkers of selecting 40 (or 20%) heavy drinking students in Jefferson High with and without consideration of their network properties at t_1

Note: 20per – Randomly selecting 20% heavy drinkers; 20peroutd – Selecting 20% heavy drinkers with highest out-degree values; 20perind – Selecting 20% heavy drinkers with highest in-degree values; 20perclo – Selecting 20% heavy drinkers with highest closeness centrality values; 20perbet – Selecting 20% heavy drinkers with highest betweenness centrality values; 20pereig – Selecting 20% heavy drinkers with highest eigenvector centrality values; 20perlcc – Selecting 20% heavy drinkers with highest local clustering coefficient values; 20perkcore – Selecting 20% heavy drinkers with highest *k*-core values; 20perbrivf – Selecting 20% heavy drinkers with highest Valente-Fujimoto version (2010) bridge measure values; 20perbriev – Selecting 20% heavy drinkers with highest Everett-Valente version (2016) bridge measure values.

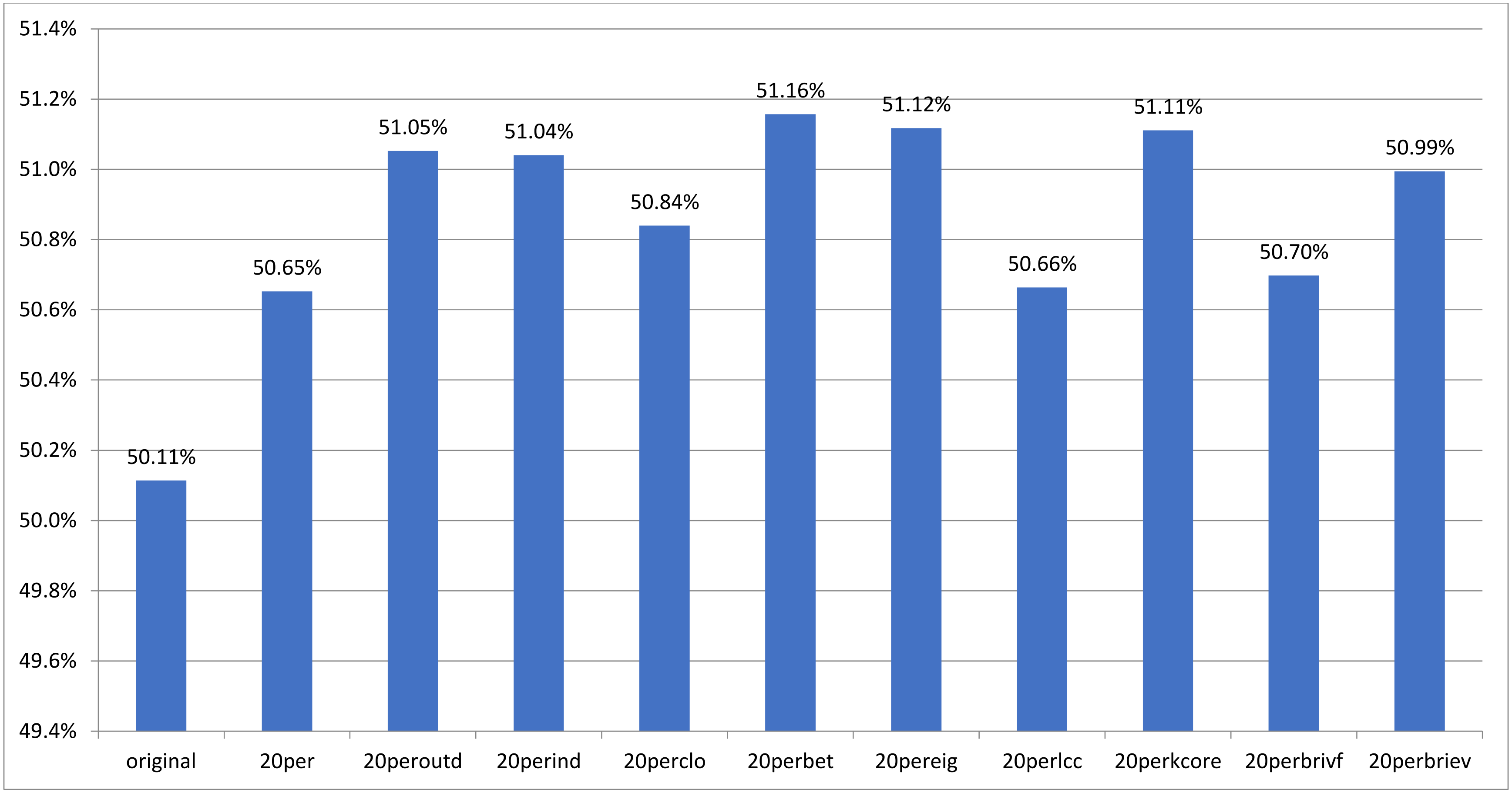

Fig. 2 The simulation results for non-drinkers of selecting 60 (or 20%) heavy drinking students in Sunshine High with and without consideration of their network properties at t_1

Note: 20per – Randomly selecting 20% heavy drinkers; 20peroutd – Selecting 20% heavy drinkers with highest out-degree values; 20perind – Selecting 20% heavy drinkers with highest in-degree values; 20perclo – Selecting 20% heavy drinkers with highest closeness centrality values; 20perbet – Selecting 20% heavy drinkers with highest betweenness centrality values; 20pereig – Selecting 20% heavy drinkers with highest eigenvector centrality values; 20perlcc – Selecting 20% heavy drinkers with highest local clustering coefficient values; 20perkcore – Selecting 20% heavy drinkers with highest k-core values; 20perbrivf – Selecting 20% heavy drinkers with highest Valente-Fujimoto version (2010) bridge measure values; 20perbriev – Selecting 20% heavy drinkers with highest Everett-Valente version (2016) bridge measure values.