Adolescent Peer Networks and the Potential for the Diffusion of Intervention Effects

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Abstract:

Many evaluation studies assess the direct effect of an intervention on individuals, but there is an increasing interest in clarifying how interventions can impact larger social settings. One process that can lead to these setting-level effects is diffusion, in which intervention effects spread from participants to non-participants. Diffusion may be particularly important when intervention participation rates are low, as they often are in universal family based prevention programs. We drew on socialization and diffusion theories to articulate how features of peer networks may promote the diffusion of intervention effects. Then, we tested the measurement properties of ten social network analytic (SNA) measures of diffusion potential. Data were from 42 networks ($n = 5,784$ students) involved in the PROSPER intervention trial. All families of sixth-grade students were invited to participate in a family based substance use prevention program, and 17 % of the families attended at least one session. We identified two dimensions of network structure—social integration and location of intervention participants in their peer network—that might promote diffusion. Analyses demonstrated that these SNA measures varied across networks and were distinct from traditional analytic measures that do not require social network analysis (i.e., participation rate, how representative participants are of the broader population). Importantly, several SNA measures and the global network index predicted diffusion over and above the effect of participation rate and representativeness. We conclude by recommending which SNA measures may be the most promising for studying how networks promote the diffusion of intervention effects and lead to setting-level effects.

Keywords: Diffusion | Peer networks | Family interventions | Substance use prevention programs | Adolescence

Article:

Many prevention programs assume that peers influence one another, yet relatively few studies have tested whether specific features of peer networks facilitate peer influence in the form of diffusion, or spread, of intervention effects beyond intervention participants. In principle, diffusion makes it possible for an intervention that is delivered to only a subset of people to have far-reaching effects on larger social settings, such as schools and communities (Gest et al. 2011; Rogers 2003). Notably, some networks may be more likely than others to support diffusion. For example, the likelihood of diffusion may depend on the proportion of the network that participated in the intervention, how socially integrated the network is, and whether intervention participants are in relatively higher status positions than their peers. Some of these network-level features can be assessed using traditional analytic measures, but other features cannot. The field of social network analysis (SNA) provides many measures that prevention scientists can use to assess different dimensions of network structure, such as social integration and location of intervention participants in the network (e.g., Valente 2010; Wasserman and Faust 1994). Previous studies have found that some SNA measures can predict the rate of diffusion (e.g., Moody 2009; Valente 1995), but more work is needed to determine whether SNA measures provide any advantages over traditional analytic measures.

In this paper, we drew on diffusion and socialization theories to identify features of school-based peer networks that may promote the diffusion of intervention effects. We identified ten SNA measures that assess different dimensions of network structure. We then tested the psychometric properties of these measures using data from 42 sixth-grade peer networks and tested whether these SNA measures predicted diffusion after controlling for the effects of the traditional analytic measures.

Network-Level Features That May Facilitate Diffusion

Diffusion may be particularly important when only a portion of a population participates in a prevention program. For example, participation rates rarely exceed 30 % for universal family based interventions offered to students at the same school (Heinrichs et al. 2005; Spoth and Redmond 2000). In the absence of diffusion, most students at the school will not benefit. There is, however, some intriguing evidence that diffusion may occur in such programs. A 1-year follow-up of the Iowa Strengthening Families Program (ISFP) indicated that intervention participants were less likely to initiate alcohol use than other students (Spoth et al. 1999). Four years later, however, students at intervention schools—regardless of whether they had participated in ISFP or not—were less likely to initiate drug use compared with students at control schools (Spoth et al. 2001). These school-wide effects suggest that attitudes and behaviors promoted by ISFP may have diffused through school-based peer networks. If so, what network-level features might have facilitated this diffusion?

Participation Rate

Even without considering diffusion, program implementers typically strive for higher participation rates to maximize direct impact of the intervention; however, participation rate may also impact diffusion processes. According to socialization theorists, deviant behavior is learned through modeling and reinforcement (e.g., Akers 1998; Dishion et al. 1996). From this perspective, the likelihood of diffusion increases with participation rates—if an intervention effectively reduces participants' deviant behavior, higher participation rates mean that more students will be exposed to peers who model and reinforce non-deviant attitudes and behavior. This perspective is consistent with diffusion theories which argue that rates of diffusion accelerate rapidly once a “critical mass,” or higher proportion, of people have adopted an innovation (Rogers 2003; Valente 1995).

Representativeness

Socialization and diffusion theories also suggest that people are more likely to model their behavior after peers who are similar to themselves (Rogers 2003). It follows that diffusion may be more likely in networks where participants are representative of the broader population in terms of salient demographic and behavioral characteristics. For example, if only non-deviant, high SES girls participate in an intervention, then diffusion of effects to boys, deviant youth, and low SES non-participants may be reduced or not occur at all.

Participation rates and representativeness are unlikely to be the only network-level features that facilitate diffusion. Consider a program being implemented in two networks with equal participation rates and with participants who are equally representative of their network populations. In one network, the participants are isolated from their peers. In the other, the participants are popular leaders. Socialization theory predicts less diffusion in the first network because far fewer non-participants will be exposed to or be open to influence from participants. Consistent with this prediction, one simulation study found that the rate and reach of diffusion was greatest when adopters were opinion leaders rather than randomly selected or marginal individuals (Valente and Davis 1999). Thus, network structure (e.g., how socially integrated the network is; where participants are located in the peer network) is also likely to impact diffusion.

Social Integration

Diffusion may be more likely in socially integrated networks, which are tightly interconnected (e.g., many social ties among members), unclustered (e.g., not divided into disconnected groups), and not hierarchical (e.g., egalitarian). For example, in highly connected networks, students have many opportunities to interact, model, and reinforce each other’s attitudes and behaviors (Valente et al. 2004), which increases the potential for intervention effects to diffuse from participants to non-participants. By contrast, when networks are highly clustered, diffusion may occur rapidly within those groups but slowly between groups (Valente 2010). Furthermore, when networks are hierarchical, people at the top of the hierarchy can act like gatekeepers and prevent the diffusion of intervention messages. Consistent with these expectations, Valente (1995) found that innovations diffused faster in highly connected networks, and Moody (2009) found that diffusion was slower in highly clustered networks where social ties were primarily to other members of the same group.

Location of Intervention Participants in the Network

Diffusion may also be more likely when a higher proportion of non-participants are exposed to the attitudes and behaviors promoted by the intervention. Such exposure may be more likely when participants are widely distributed across the network, such that a greater proportion of non-participants are connected to participants, either directly (as members of the same group or as friends) or indirectly (as friends of friends). Such exposure may also be more likely when participants occupy more central, higher status positions within the network compared with their peers. In such networks, participants are in a better position to set network-level social norms and to model attitudes and behaviors promoted by the intervention. Consistent with this latter expectation, interventions that use high status peers, or opinion leaders, to diffuse intervention messages are often effective (e.g., Campbell et al. 2008; Kelly et al. 1997; Latkin 1998; Miller-Johnson and Costanzo 2004; Valente et al. 2003; Wyman et al. 2010).

Present study

In this paper, we tested the psychometric properties of ten SNA measures of diffusion potential. For these SNA measures to be useful tools, they must vary across networks, capture relatively stable dimensions of the network, and be related to each other in expected ways. These SNA measures should also be distinct from traditional analytic measures, such as participation rate and representativeness. Finally, these SNA measures should predict diffusion over and above the effect of more traditional analytic measures. We hypothesized that diffusion would be more likely in networks that were highly connected, generally unclustered, and less hierarchical, as well as in networks where participants were distributed across the network and in networks where participants were in relatively higher status positions than non-participants.

We tested our hypotheses using data from a community intervention trial that included a family based substance use prevention program as one component. We assessed network structure at baseline (pretest) and shortly after the intervention ended (posttest) and tested whether measures at each of these assessments predicted diffusion 1 and 2 years later. Because diffusion is a slow process (e.g., Rogers 2003; Valente 2010), we hypothesized that the measures would be more predictive of diffusion at the 2-year follow-up. In addition, because interventions may impact network structure (e.g., Gest et al. 2011), we hypothesized that the posttest SNA measures would be more predictive of diffusion than the pretest measures.

Method

Setting, Design, and Sample

Two successive sixth-grade cohorts from 28 rural communities in Pennsylvania and Iowa participated in the PROmoting School-community-university Partnerships to Enhance Resilience (PROSPER) project (Spoth et al. 2004). Within each state, researchers randomly assigned seven communities to the intervention condition. Early in Spring of sixth grade, all students at the intervention schools and their families were invited to participate in the Strengthening Families Program for Parents and Youth 10–14 (SFP10-14; Molgaard et al. 1987), which targets risk factors of early substance use. During the seven weekly sessions, parents and youth met separately for an hour and then met together for an hour to practice parent–child communication and engage in activities to improve family cohesiveness. In seventh grade, all students at the intervention schools participated in one of three different school-based substance use prevention programs. All students completed a baseline survey in Fall of sixth grade (pretest) and surveys in Spring of sixth grade (posttest), Spring of seventh grade (1-year follow-up) and Spring of eighth grade (2-year follow-up). Students completed surveys only if they assented and if their families did not return a form exempting them from the study.

We focused on the sixth-grade peer networks at the intervention schools (pretest and posttest assessments). Some communities had more than one school with sixth graders, and some schools experienced transitions between cohorts (e.g., a fire in one building), yielding 47 "school-cohorts" or networks across 26 intervention schools. We excluded one network that did not collect friendship nominations and four networks that had zero or one SFP10–14 participant. Data were provided by 5,784 sixth graders (M = 11.8 years; 49.6 % female) who were in the remaining 42 networks during the 2001–2002 (cohort 1) or 2002–2003 (cohort 2) school years. To test the predictive validity of the measures, we also used behavioral data from these students at the 1- and 2-year follow-up assessments. Most students (72.6 %) completed surveys at all four assessments; 16.9 % completed surveys at only three assessments; 6.4 % completed surveys at only two assessments, and 4.1 % completed surveys at only one assessment. On average, SFP 10–14 participants completed the survey at more assessments (M = 3.76 assessments) than non-participants (M = 3.55 assessments). Sample demographics reflected the communities in which the students lived: 82.0 % of students described themselves as White, 6.2 % as Hispanic, 2.3 % as Black, 1.1 % as Asian, and 8.4 % as another race/ethnicity. One third of the students received free or reduced lunch, and 77.3 % of the students lived with two parents.

Measures

Traditional Analytic Measures

Participation Rate

We calculated the proportion of students in each network who participated in at least one SFP10–14 session. The average participation rate was higher than the rate that is typically observed for universal family based interventions: 17 % of students (n = 1,064) and their families participated (Spoth et al. 2007). In the current study, we only included n = 862 participants (81 %) whose families provided consent for project staff to record their attendance. Of these students, 825 were in one of the 42 focus networks at pretest or posttest.

Representativeness

If participants are representative of their peers, they should be similar to non-participants with respect to demographic and behavioral characteristics. Thus, we compared the average characteristics of the participants and non-participants in each network, using the difference in proportion scores for binary measures and Cohen's D measure of effect size for continuous measures. Values further from 0 in either direction indicated a larger difference between participants and non-participants; thus, we calculated the absolute value of each score and multiplied it by −1 so that higher scores indicated greater representativeness.

Demographic Characteristics.

Students self-reported their gender (1 = male, 0 = female) and their free lunch status (1 = typically receive free or reduced lunch on school days, 0 = other).

Behavioral Characteristics

Students self-reported their typical grades (1 = "Mostly lower than D's" to 5 = "Mostly A's (90–100)") and how many times in the past year they had engaged in 12 delinquent behaviors (e.g., "Taken something worth less than $25 that did not belong to you"; 1 = "Never" to 5 = "Five or more times"). We computed a delinquency score from these 12 items using item response theory scaling (see Osgood et al. 2002). We also computed a measure of substance use attitudes by standardizing and averaging four subscales: attitudes toward substance use, expectation for substance use, substance use refusal intentions, and substance refusal efficacy. Higher scores indicate anti-substance use attitudes.

Average Representativeness

We created an average representativeness score by standardizing each representativeness measure and calculating the average of these scores.

SNA Measures

Students identified up to two best friends and up to five other close friends in the same grade at the same school. The survey completion rate—the proportion of students in each network that provided friendship nominations—was generally high—M Pretest = 0.74 (range, 0.41–1); M Posttest = 0.78 (range, 0.55–0.95). From these nominations, we calculated ten SNA measures (see Appendix 1 and 2 for formulas) and identified friendship groups, or groups of students within the network who had similar patterns of friendship nominations; group boundaries were drawn so as to maximize the number of within-group social ties compared with the number of between-group social ties (see Kreager et al. 2011).

Social Integration

Connectivity

In highly connected networks, there are many social ties among students. Such networks are structurally cohesive: They are connected by multiple independent relational paths linking all pairs of students in the network (Moody and White 2003). The large number of social ties typically reduces the number of nominations needed for one student to reach another student. Therefore, we operationalized connectivity in two ways. Structural cohesion was the mean number of "node-independent paths" (i.e., undirected relational paths connecting two students that do not go through the same students) across all pairs of students (Moody and White 2003). Social distance was the smallest number of nominations (i.e., "geodesic" distance) between each pair of students, averaged across all pairs (Wasserman and Faust 1994).

Clustering

In highly clustered networks, students form tightly bounded groups, developing friendships primarily with other students who are in their group. We operationalized clustering in two ways. Freeman's segregation index captured the extent to which students were only friends with peers in their own group (Freeman 1978). In a completely clustered network, all friendship nominations are to other group members, and the segregation index is 1; in a network with randomly distributed nominations, the segregation index is 0. We also used the transitivity ratio, the proportion of indirect friendships that were also direct friendships or the degree to which a person's friends were friends with one another (Wasserman and Faust 1994). Using the transitivity ratio to measure clustering may seem counterintuitive: Hypothetically, if everyone was friends with everyone else, the transitivity ratio would be 1 and there would be no clustering. In real networks, however, friendships are limited: Each tie that leads to a closed triad occurs at the expense of a tie to another student outside that triad, thus increasing clustering.

Hierarchy

In hierarchical networks, only a few students are located at the center of the network. When the network center is based on indegree, the most central students receive the most friendship nominations. When the network center is based on betweenness, the most central students connect many students, often bridging otherwise disconnected pairs of students (i.e., they lie along a relatively high number of the shortest paths between other pairs of students in the network). Here, we operationalized hierarchy as the difference in centrality between the most central student in the network and all other students (Freeman 1979), defining centrality both in terms of indegree and betweenness. In theory, both indegree centralization and betweenness centralization can range from 0 (when all students in the network are equally central) to 1 (when a single student is at the center of the network, meaning the network is completely hierarchical).

Location of the Intervention Participants in the Network

Distribution of Participants in the Network

When intervention participants are evenly distributed throughout the network, a greater proportion of non-participants should be connected to participants. These connections could occur, for example, if most groups have at least one intervention participant as a member (rather than intervention participants clustering in the same few groups), and if most non-participants are either friends or friends of friends with an intervention participant. Therefore, we operationalized the distribution of participants in the network as the proportion of groups with at least one SFP10–14 participant and as the proportion of non-participants within two steps of an SFP10–14 participant (i.e., they either named a participant as a friend [one step] or named someone who named a participant [two steps]).

Participants' Relative Status

Because of their high status, central location within the network, students who are named frequently as friends (i.e., high indegree centrality) and students who bridge otherwise disconnected students (i.e., high betweenness centrality) may be particularly influential. Therefore, in networks where participants on average have higher indegree and betweenness centrality than non-participants, the participants may be in a better position to set network-level norms and influence their peers. To assess participants' relative status compared with their peers, we compared participants and non-participants average indegree and betweenness centrality, using Cohen's D measure of effect size to quantify these differences.

Global Network Index.

We computed a global network index that placed equal weight on each of the network measures by regressing each network measure on network size and survey completion rate and saving the standardized residual. Then, we multiplied measures that we hypothesized to be negatively related to diffusion potential (i.e., social distance, clustering, and hierarchy measures) by −1 and computed the average across all ten standardized residuals.

Substance use Diffusion

If diffusion occurs, intervention participants and non-participants should become more similar over time, as the non-participants adopt behaviors promoted by the intervention (or fail to adopt behaviors discouraged by the intervention). We used Cohen's D to compare substance use between participants and non-participants at the 1- and 2-year follow-up assessments. We computed substance use scores using item response theory scaling (see Osgood et al. 2002) for four items: How often in the past month students had used cigarettes, used alcohol, been drunk, and used marijuana (1 = "Not at all" to 5 = "More than once a week"). We multiplied the absolute value of each score by −1, such that higher scores indicated more similarity in substance use between participants and non-participants, and thus more diffusion. Several of the networks that were separate in sixth grade merged as students moved into seventh or eighth grade. To determine whether network structure at the time when SFP10-14 was implemented predicted diffusion, we calculated diffusion scores for each network based on which network the students had been in during sixth grade.

Results

Variation Across Networks

Both participation rates and representativeness varied across networks (top of Table 1). Notably, even though participants were on average representative of their non-participating classmates, representativeness varied across networks. For example, the mean Cohen's D for delinquency was −0.03 at pretest, but ranged from −0.83 to 0.99, indicating that, in some networks, there was over 0.5 SD difference in the mean delinquency of participants and non-participants.

	Pretest (n=42 networks)				Posttest (n=40 networks)[a]			
	Mean	SD	Min	Max	Mean	SD	Min	Max
	Traditional analytic measures							
Participation rate	0.14	0.09	0.05	0.46	0.15	0.10	0.04	0.53
Representativeness								
Demographic representativeness								
Gender[b]	−0.02	0.20	−0.47	0.42	−0.02	0.20	−0.50	0.46
Free lunch[b]	−0.05	0.20	−0.42	0.44	−0.05	0.19	−0.71	0.41
Behavioral representativeness								
Grades[c]	0.05	0.30	−0.58	0.86	0.04	0.57	−2.58	1.03
Delinquency[c]	−0.03	0.42	−0.83	0.99	0.00	0.49	−1.08	1.30
Substance use attitudes[c]	0.03	0.33	−1.06	0.59	0.00	0.41	−1.06	0.72
	SNA measures							
Social integration								
Connectivity								
Structural cohesion	2.51	0.67	1.23	3.96	2.82	0.68	1.35	4.06
Social distance	4.49	1.39	1.80	9.05	4.30	1.15	1.85	6.85
Clustering								
Segregation index	0.70	0.07	0.56	0.95	0.70	0.10	0.57	0.96
Transitivity ratio	0.34	0.09	0.21	0.60	0.34	0.08	0.20	0.57
Hierarchy								
Indegree centralization	0.08	0.04	0.02	0.16	0.09	0.04	0.02	0.20
Betweenness centralization	0.10	0.05	0.02	0.20	0.10	0.04	0.02	0.23
Location of the intervention participants in the network								
Distribution of participants in the network								
Prop. of groups with 1+ part.	0.65	0.24	0.09	1.00	0.67	0.25	0.00	1.00
Prop. within two steps of a part.	0.48	0.19	0.07	0.89	0.54	0.19	0.08	0.88
Participants' relative status								
Indegree[c]	−0.07	0.41	−0.94	0.89	−0.01	0.34	−0.69	0.71
Betweenness[c]	0.11	0.47	−0.80	1.72	0.15	0.42	−0.88	1.00

Table 1. Descriptive information for traditional analytic measures and SNA measures of diffusion potential

Prop. proportion, part. intervention participant

a The posttest sample size was 40 networks, because two networks did not administer a posttest survey. The measures that relied on student survey data (i.e., free lunch status, grades, delinquency, substance use attitudes) had n=39 at posttest because one network did not have any survey data from SFP10– 14 participants in that network at that assessment

b Measure scored as the difference in proportions between participants and non-participants. Positive values indicate that participants were higher than non-participants on that measure

c Measure scored as the Cohen's D effect size between participants and non-participants. Positive values indicate that participants were higher than nonparticipants on that measure

The SNA measures also varied across networks (bottom of Table 1). For example, at pretest, structural cohesion ranged from 1.23 to 3.96, thus students were connected to their peers through one to four independent paths on average. Social distance, the average number of steps between each pair of non-isolated students, ranged from under two steps to over nine steps. The transitivity ratio and segregation index indicated that 21–60 % of all indirect friendships were also direct friendships, and 56–95 % of all friendships were with peers within the same group. The networks were not hierarchical (both centralization scores < 0.20), but hierarchy varied across networks. The proportion of groups with at least one SFP10–14 participant ranged from 0.09 to 1, and the proportion of non-participants within two steps of an SFP10-14 participant ranged from 0.07 to 0.89. In some networks, SFP10–14 participants had higher status (i.e., Cohen's $D > 0.50$) whereas, in other networks, non-participants had higher status (i.e., Cohen's $D < -0.50$).

Stability and Convergent Validity of SNA Measures of Diffusion Potential

We assessed within-year stability of the measures by correlating the pretest and posttest scores, controlling for network size and survey completion rate (partial correlations along the diagonal in Table 2). All measures except betweenness centralization exhibited significant within-year stability. Relative status in terms of betweenness centrality was only moderately stable (r = 0.35), but the remaining stability correlations were relatively strong (r = 0.45 to r = 0.79).

	Struct. Coh.	Social Dist.	Seg. Index	Trans. Ratio	Indegree Central.	Betwn. Central.	Prop. Groups	Prop. Within 2 Steps	Indegree	Betwn.
Social Integration										
Connectivity										
Structural Cohesion	0.74***	0.30†	-0.30†	-0.34*	-0.29†	0.33*	0.30†	0.40*	-0.36*	-0.42**
Social Distance	0.37*	0.45**	-0.19	-0.34*	-0.11	0.58***	0.05	0.12	-0.05	0.13
Clustering										
Segregation Index	-0.48**	-0.08	0.71***	0.74***	0.31†	-0.12	0.12	-0.05	0.34*	0.29†
Transitivity Ratio	-0.52**	-0.30†	0.78***	0.68***	0.54***	-0.17	0.02	-0.24	0.24	0.22
Hierarchy										
Indegree Centralization	-0.36*	-0.44**	0.20	0.40*	0.54***	0.30†	0.23	-0.08	-0.01	0.09
Betweenness Centralization	0.33*	0.66***	-0.08	-0.07	-0.16	0.16	0.29†	0.17	-0.33*	-0.14
Location of the Intervention Participants in the Network										
Distribution of Participants in the Network										
Prop. of Groups with 1+ Part.	0.36*	0.15	-0.04	0.02	0.17	0.22	0.69***	0.76***	0.01	-0.07
Prop. within 2 Steps of a Part.	0.51**	0.39*	-0.29†	-0.29†	-0.11	0.36*	0.70***	0.74***	0.18	-0.14
Participants' Relative Status										
Indegree[a]	-0.19	0.16	0.15	0.09	-0.03	-0.06	0.03	0.27	0.79***	0.54***
Betweenness[a]	-0.05	0.08	0.17	0.25	0.29	-0.02	0.34*	0.09	0.33*	0.35*

Table 2. Convergent validity: partial correlations among SNA measures of diffusion potential Survey participation and network size were partialed out of all scores. Values above the diagonal are pretest correlations, values below the diagonal are posttest correlations. Values along the diagonal are the correlations between pretest and posttest

Prop. proportion, *part.* intervention participant

[a]Measure was scored as the Cohen's *D* effect size between participants and non-participants. Positive values indicate that participants were higher than non-participants with respect to that measure

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

We assessed convergent validity by correlating the SNA measures with each other at pretest (above the diagonal) and posttest (below the diagonal), controlling for network size and survey completion rate. Four of the five pairs of measures assessing the same construct (thin-lined boxes) were positively correlated at both assessments. The two hierarchy measures were positively correlated at pretest ($r = 0.30$), but not posttest. In general, the social integration measures (upper left dark-lined box) were correlated in the expected direction, but the location measures (lower right dark-lined boxes) were not related. There were few significant correlations between the social integration and location measures (lower left and upper right corners); only structural cohesion and the distribution measures were statistically related at both assessments.

Discriminant Validity of SNA Measures of Diffusion Potential

We assessed discriminant validity (Table 3) by correlating the traditional analytic and SNA measures, controlling for network size and survey completion rate. In most cases, the social integration measures were not significantly correlated with the traditional analytic measures; only structural cohesion and representativeness for delinquency were significantly correlated in the same direction at both assessments. By contrast, both distribution measures were positively correlated with participation rate, several of the representativeness measures (most consistently with gender and grades), and with average representativeness. The relative status measures were negatively correlated with representativeness for gender but not consistently related to the other traditional analytic measures. The global network index was moderately positively correlated with participation rate but was not significantly correlated with the representativeness measures.

Table 3 Discriminant validity: partial correlations among traditional analytic and SNA measures of diffusion potential

			Demographic representativeness				Behavioral representativeness							
	Participation rate		Gender[a]		Free lunch[a]		Grades[b]		Delinquency[b]		Substance use attitudes[2]		Average representativeness	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Social integration														
Connectivity														
Structural cohesion	0.10	0.24	0.23	0.22	0.07	0.14	−0.10	0.19	0.30†	0.33*	0.23	0.19	0.22	0.36*
Social distance	−0.18	−0.03	0.08	0.33*	−0.14	0.08	−0.25	0.46**	0.01	0.34*	−0.15	−0.05	−0.14	0.40*
Clustering														
Segregation index	0.16	0.11	−0.17	−0.12	0.11	0.04	0.08	−0.07	−0.14	−0.09	0.06	−0.05	−0.02	−0.12
Transitivity ratio	0.15	0.16	−0.19	−0.17	−0.04	0.23	0.06	−0.30†	−0.06	−0.02	−0.05	0.17	−0.08	−0.08
Hierarchy														
Indegree central	0.17	0.06	0.05	−0.08	−0.22	0.08	−0.02	−0.28†	−0.09	−0.34*	−0.05	0.08	−0.10	−0.16
Betweenness central	0.00	0.14	0.24	0.43**	−0.37*	0.28†	−0.22	0.35*	−0.17	0.22	−0.03	−0.12	−0.17	0.40*
Location of the intervention participants in the network														
Distribution of participants in the network														
Prop. of groups with 1+ part.	0.73***	0.68***	0.44**	0.45**	0.24	0.56***	0.33*	0.20	0.17	0.18	0.21	0.24	0.43**	0.55***
Prop. within two steps of a part.	0.70***	0.58***	0.45**	0.36*	0.19	0.31†	0.29†	0.37*	0.17	0.33*	0.37*	0.02	0.45**	0.38*
Participants' relative status														
Indegree	0.27†	0.15	−0.29†	−0.33*	−0.03	−0.17	−0.02	0.29†	−0.18	0.05	−0.13	0.05	−0.20	−0.17
Betweenness	−0.10	0.05	−0.35*	−0.04	0.00	−0.15	−0.15	−0.18	−0.30†	−0.15	−0.37*	0.02	−0.36*	0.04
Global network index	0.39*	0.32†	0.08	0.02	0.31†	−0.05	0.18	0.15	0.15	0.14	0.12	0.10	0.26	0.16

Survey participation and network size were partialed out of all scores Central centralization, prop. proportion, part. intervention participant

a Measure was scored as the absolute value of the difference in proportions between participants and non-participants. Scores were multiplied by −1 so that positive values indicate more representativeness with respect to this attribute b Measure was scored as the absolute value of the Cohen's D effect size between participants and non-participants. Scores were multiplied by −1 so that positive values indicate more representativeness †p<0.05;**p<0.001

To further illustrate the distinctiveness of the SNA and traditional analytic measures, we provide plots of two pretest networks in Fig. 1. Both networks were similar in terms of the traditional analytic measures: They had identical participation rates (22 %) and were similarly representative in terms of gender, free lunch status, delinquency, and substance use attitudes. Notably, however, their network structure differed considerably. For example, Network 1 ranked 27th on the global network index whereas Network 2 ranked first.

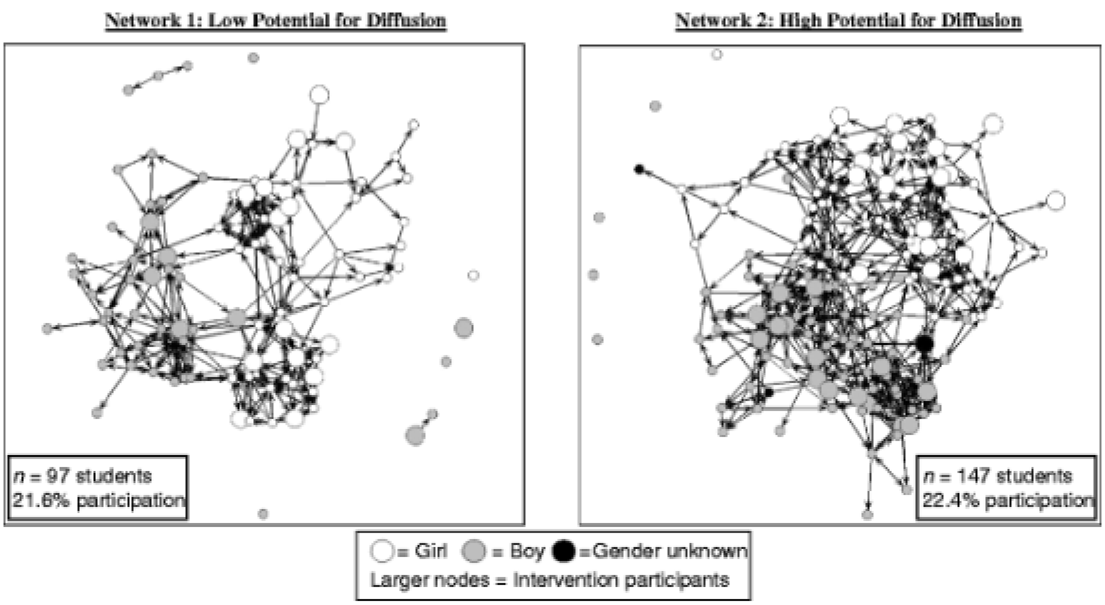

Fig. 1. These plots show the pretest friendship nominations (directional arrows) among sixth-grade students in two networks and highlight the discriminant validity between the traditional analytic measures and SNA measures of diffusion potential. Both Network 1 (left) and Network 2 (right) had similar participation rates and were similarly representative in terms of gender (Net 1 = −0.15; Net 2 = −0.06), free lunch status (Net 1 = −0.24; Net 2 = −0.15), delinquency (Net 1 = −0.03; Net 2 = −0.06), and substance use attitudes (Net 1 = −0.08; Net 2 = −0.05), but they have very different network structure. Network 1 ranked 27th on the global network index whereas Network 2 had the highest rank. Compared with Network 2, Network 1 was less cohesive (Net 1 = 2.85 vs. Net 2 = 3.69) and more clustered (e.g., segregation index, Net 1 = 0.73 vs. Net 2 = 0.63). Several participants in Network 1 were isolated from the network, and overall the participants received fewer friendship nominations (e.g., Cohen's D for indegree, Net 1 = 0.09 vs. Net 2 = 0.32). As a result, Network 1 also had fewer non-participants within two steps of an SFP10–14 participant compared with Network 2 (58 % vs. 82 %)

Predictive Validity of SNA Measures of Diffusion Potential

To assess predictive validity, we correlated each measure with substance use diffusion at the 1- and 2-year follow-up assessments, controlling for the pretest (or posttest) measure of substance use diffusion and 1- or 2-year network size and survey participation rate (Table 4). We controlled for participation rate in all analyses (except for participation rate), and we also controlled for average representativeness for the analyses of the SNA measures.

	1 -year follow-up		2-year follow-up	
	Pretest	Posttest	Pretest	Posttest
	Traditional analytic measures			
Participation rate	0.26	0.20	0.45**	0.43**
Representativeness				
Demographic representativeness				
Gender	−0.30†	−0.17	0.19	0.09
Free lunch	0.19	−0.10	−0.14	−0.17
Behavioral representativeness				
Grades	−0.04	0.35*	−0.26	0.36*
Delinquency	−0.03	0.13	0.05	0.05
Substance use attitudes	0.21	−0.13	0.17	−0.37*
Average representativeness	−0.02	−0.03	−0.06	0.16
	SNA measures			
Social integration				
Connectivity				
Structural cohesion	−0.08	0.35*	0.30†	0.57***
Social distance	−0.20	0.34†	0.15	0.28
Clustering				
Segregation index	0.16	−0.20	−0.13	−0.36*
Transitivity ratio	−0.09	−0.31†	−0.22	−0.53***
Hierarchy				
Indegree centralization	−0.31†	−0.46**	−0.25	−0.09
Betweenness centralization	−0.26	0.05	0.20	0.04
Location of the intervention participants				
Distribution of participants across the network				
Prop. of groups with 1+ part.	0.01	0.13	0.19	0.25
Prop. within two steps of a part.	−0.03	0.13	0.36*	0.45**
Participants' relative status				
Indegree	0.09	0.09	−0.06	0.02
Betweenness	0.04	0.09	−0.44*	0.12
Global network index	0.36*	0.49**	0.09	0.35*

Table 4 Predictive validity: partial correlations between diffusion measures and substance use diffusion

Substance use diffusion was defined as −1* (absolute difference in substance use between participants and non-participants), such that higher scores= higher diffusion. All analyses partial out network size and survey participation rate at either the 1- or 2-year follow-up, and substance use representativeness at either pretest or posttest. All analyses except for participation rate also controlled for SFP10–14 participation rate Prop. proportion, part. intervention participant

†p<0.001

Participation rate positively predicted diffusion at the 2-year follow-up as did the posttest measure of representativeness for grades. The other representativeness measures, including average representativeness, were either uncorrelated or *negatively* correlated with diffusion. By contrast, several of the SNA measures predicted diffusion in the expected direction: Structural cohesion and the proportion of participants within two steps of a participant were positively correlated with diffusion and the clustering measures and indegree centralization were negatively correlated with diffusion. In general, prediction was stronger for the posttest measures and at 2-year follow-up. Finally, the global network index positively predicted diffusion at 1-year follow-up and from posttest to 2-year follow-up.

Discussion

Prevention scientists have drawn on diffusion theory to identify opinion leaders for interventions targeting a wide array of behaviors, including risky drug and sex behaviors (e.g., Campbell et al. 2008; Latkin 1998; Valente et al. 2003); delinquency (e.g., Miller-Johnson and Costanzo 2004), and suicide (e.g., Wyman et al. 2010). In the present study, we identified two dimensions of network structure—social integration and location of participants in the network—that might facilitate such diffusion efforts, and we identified ten SNA measures that could capture these features. Overall, the SNA measures demonstrated sufficient variability, stability, and convergent, discriminant, and predictive validity to suggest their potential utility in studies of diffusion processes. Thus, our study contributes to the small, but rapidly growing literature that tries to clarify how interventions may promote setting-level changes (Gest et al. 2011; Tseng and Seidman 2007). Specifically, these SNA measures provide one way to assess how a family based intervention may translate into changes in social processes within schools. Below, we discuss the degree to which our results supported our hypotheses and provide recommendations for prevention scientists about which SNA measures may be more promising for future research.

Diffusion Potential Based on Social Integration and Participant Location in the Network

Socialization and diffusion theories agree that diffusion should vary as a function of the social integration of the network. In addition, the location of participants in the peer network may impact the extent to which non-participants are indirectly exposed to the intervention’s effects. All ten SNA measures varied across networks, but patterns of stability, convergent validity, and predictive validity differed across measures.

Connectivity

As hypothesized, diffusion was higher in more structurally cohesive networks where students were connected through many independent paths. The presence of these paths may have provided more opportunities for participants to transmit attitudes and behaviors to non-participants, even if some students did not adopt them. By contrast, diffusion may have been hindered in less cohesive networks because transmission depended on each person along a path adopting attitudes and behaviors promoted by the intervention. Contrary to expectation, however, there was a non-significant positive trend between structural cohesion and social distance, suggesting that the average distance between students may be greater in more cohesive networks. This unexpected correlation may be driven by other network features (e.g., less cohesive networks were more clustered, which may have decreased the average number of steps between students). In light of this unexpected correlation, it is not surprising that posttest social distance was positively correlated with diffusion at 1-year follow-up. Given the strong theory and empirical evidence linking structural cohesion to network dynamics (Moody and White 2003), its greater stability, and its stronger correlation with diffusion, prevention scientists may find that structural cohesion is a more promising connectivity measure than social distance.

Clustering

As hypothesized, clustering appeared to slow the diffusion of intervention effects. Specifically, diffusion was less likely in networks where students had few friendships outside of their own groups (high segregation index) and in networks where students were friends with their friends' friends (high transitivity ratio). This negative relationship was stronger and more consistent for the transitivity ratio. Both measures demonstrated moderately strong convergence and stability, but given that the transitivity ratio does not require researchers to identify groups and given its stronger correlation with diffusion, prevention scientists may find that the transitivity ratio is a more promising clustering measure than the segregation index.

Hierarchy

As hypothesized, indegree centralization negatively predicted diffusion at 1-year follow-up. Diffusion may have been less likely in highly centralized networks because hierarchy slows diffusion, as people at the top have the potential to act like gatekeepers and prevent intervention messages from diffusing. Notably, indegree and betweenness centralization were correlated only at pretest and only indegree centralization was reliably stable. Thus, indegree centralization may be a better measure to use for studying diffusion in adolescent peer networks. Future studies should, however, explore whether the effect of hierarchy on diffusion depends on the status of the participants: If high status students participate in the intervention, then hierarchy may actually promote, rather than hinder, diffusion (Valente 2010).

Distribution of Participants in the Network

Notably, only the proportion of non-participants within two steps measure significantly predicted diffusion and only at the 2-year follow-up. The weaker-than-expected predictive validity likely reflects the strong correlations between both distribution measures and participation rate (indeed, in preliminary analyses that did not control for participation rate, both measures predicted diffusion). The correlation between the distribution measures and participation rate is not surprising: when many students participate in the intervention, there are more opportunities for non-participants to be directly or indirectly connected to them. Although the distribution measures may not add much unique predictively, they may help to explain how a higher participation rate leads to diffusion—when participants are distributed throughout the network, rather than friends only with each other, more non-participants may be exposed to the attitudes and behaviors promoted by the intervention.

Participants' Relative Status

Contrary to our hypotheses, neither of the relative status measures was positively related to diffusion, even though they both demonstrated moderately strong convergence and stability. This lack of predictive validity is surprising, given the success of interventions that target high status opinion leaders. Notably, however, SFP10–14 does not target or train opinion leaders, thus even when high status students participated in SFP10–14, they were not taught how to promote intervention messages among their peers. In addition, we only measured exposure and not adoption, so it is possible that, in some networks, high status students who participated in SFP10–14 did not adopt the intervention attitudes and behaviors and thus did not facilitate diffusion. In addition, relative status in terms of betweenness centrality at pretest negatively predicted diffusion at 2-year follow-up. This negative relationship may indicate that students who are on the shortest path between many pairs of students are actually on the periphery of several groups and not in a position to influence students in these groups. Future studies should continue to explore the predictive validity of both measures and consider alternative metrics for assessing the status and potential influence of intervention participants.

Timing of Diffusion

Overall, our results provided some support for our hypothesis that predictive validity was stronger when diffusion was evaluated 2 years after the intervention. This result is consistent with the premise that diffusion is a slow process, if it occurs at all. In addition, there was some evidence that the posttest measures of network structure were better predictors of diffusion. This result indicates that the intervention may have impacted network structure in some networks, putting them in a better position to facilitate diffusion.

Limitations and Future Directions

Several of this study's methodological limitations should be noted. First, the sample of 42 networks from nonurban communities was larger than most network-level studies but may not be representative of networks in all schools, particularly those in large, urban districts. The sample size also precluded us from testing whether some SNA measures were better predictors of diffusion than others and testing whether some network features moderate the effect of other features. For example, clustering may hinder diffusion if participants were concentrated in a few groups but not if they were evenly distributed throughout the network.

Second, students could nominate only same-grade students at their school, but out-of-school friends may be particularly influential for some youth (Kiesner et al. 2004). These restrictions are less pertinent in this study, however, given our focus on the school-wide diffusion of effects from a family based intervention offered to a school-grade cohort.

Third, most of the SNA measures were based on directed, or "sent," social ties. We based this decision on a long tradition in theory (e.g., reference group theory; see Newcomb 1950; Sherif 1948) and research (see Veenstra et al. 2013; Warr 2002) that assumes that peer influence is directional: People are influenced by those who they choose as friends. Because diffusion is expected to be the result of peer influence processes, we believe that this was the best choice for constructing SNA measures. Directed social ties, however, may be unidirectional (i.e., unreciprocated), and these social ties may be weaker than reciprocated social ties. Future research should explore whether measures based on reciprocated social ties or measures that incorporate some metric of relationship quality also predict diffusion processes.

Finally, several factors may have weakened the predictive validity of the SNA measures. In particular, some networks merged as students transitioned from elementary to junior high school. To address this problem, we defined network-level measures based on which network a student was in during sixth grade. This approach is justified, given that, in the year after a merger, students largely interact with peers from their former network (Temkin et al. 2012), but future studies should explore what happens when networks with different propensities for diffusion merge. Notably, despite these mergers, several SNA measures still predicted diffusion, underscoring the potential value of these measures in future research.

Summary

We argued that evaluation studies should explore whether intervention effects can diffuse through peer networks, thereby extending the impact of the intervention beyond the direct effects on individual participants. Such diffusion effects would be particularly important when only a small proportion of a population participates in an intervention (as is the case in most family based interventions) and when interventions strategically target a few opinion leaders to deliver intervention messages to a wider audience. Although previous studies have drawn on diffusion theory to design and evaluate intervention programs, less research has focused on identifying the specific features of peer networks that might facilitate diffusion. We identified ten SNA measures to capture several potential avenues of diffusion and demonstrated that these measures were stable across a school year and generally uncorrelated with participation rates and representativeness. More importantly, several of the SNA measures and the global network index predicted diffusion, even after controlling for participation rate and representativeness. By contrast, participation rate only predicted diffusion at 2-year follow-up, and average representativeness did not predict diffusion at either assessment. In conclusion, although traditional analytic measures are relatively easy to compute, they do not fully capture some network-level features that can facilitate or hinder diffusion. Future research can use these SNA measures to further clarify how network structure facilitates diffusion, which in turn could inform efforts to enhance the reach of prevention programs.

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ELECTRONIC SUPPLEMENTARY MATERIALS OMITTED FROM THIS FORMATTED DOCUMENT

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