Published in final edited form as:

Prev Sci. 2011 December ; 12(4): 349–360. doi:10.1007/s11121-011-0229-2.

Strengthening Prevention Program Theories and Evaluations: Contributions from Social Network Analysis

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Abstract

A majority of school-based prevention programs target the modification of setting-level social dynamics, either explicitly (e.g., by changing schools' organizational, cultural or instructional systems that influence children's relationships), or implicitly (e.g., by altering behavioral norms designed to influence children's social affiliations and interactions). Yet, in outcome analyses of these programs, the rich and complicated set of peer network dynamics is often reduced to an aggregation of individual characteristics or assessed with methods that do not account for the interdependencies of network data. In this paper, we present concepts and analytic methods from the field of social network analysis and illustrate their great value to prevention science – both as a source of tools for refining program theories and as methods that enable more sophisticated and focused tests of intervention effects. An additional goal is to inform discussions of the broader implications of social network analysis for public health efforts.

Keywords

Peers; Social networks; program theory; evaluation

Concepts and measures from social network analysis have played little explicit role in the development and evaluation of prevention programs, but they have great potential to contribute to this work. School-based prevention efforts often promote changes in peer relationships and behavioral norms within a classroom or school setting, both of which are relevant to social network analysis. In some programs, there is a direct attempt to alter these setting-level social network dynamics by reorganizing systems of instruction, behavior management or teacher-student advising (Battistich, Schaps, Watson & Solomon, 2000; Felner et al., 1993; Jalongo, Poduska, Werthamer & Kellam, 2001; Stevens & Slavin, 1995). In other programs, setting-level peer effects emerge as a byproduct of efforts to alter norms or promote skills among all individuals within a setting (Botvin & Griffin, 2004; CPPRG, 1999). In most prevention program studies, setting-level social network dynamics have been conceptualized and measured by aggregating individual-level measures across all participants in the setting. Though this approach can be useful, it precludes attention to setting-level dynamics of the social network that cannot be reduced to individual-level phenomena (Tseng & Seidman, 2007). Here we propose an initial step in integrating social network analysis with prevention research by using the conceptual and methodological tools of social network analysis to define setting-level variables characterizing peer network processes that may be relevant to common school-based prevention strategies.

Relevance of Setting-Level Social Network Dynamics to School-Based Prevention Efforts

Setting-level social network dynamics are most obviously relevant to interventions that explicitly attempt to reorganize school-based social systems of relationships and behavioral norms among actors (i.e., interventions that explicitly aim to reorganize social networks). Some interventions reorganize relationships between and among teachers and students to promote stronger social ties and feelings of social belonging. For example, classroom meetings and cross-grade activities can be employed to promote a sense of community (Battistich et al., 2000); or schools can be divided into smaller instructional and advising sub-units to promote closeness in teacher-student and peer relationships (Felner et al., 1993). Other interventions reorganize relationships among students to reduce rates of negative social experiences or to promote social integration. For example, Olweus' (1993) bullying-prevention program involves efforts to shift social norms regarding bullying through coordinated actions across the individual, classroom and school levels. Cooperative learning groups are often structured to promote stronger connections among all youth and to increase the social integration of otherwise marginalized or segregated groups of individuals (Stevens & Slavin, 1995). In each of these cases, prevention efforts explicitly and directly target social network dynamics in the classroom or school social setting.

Setting-level social network dynamics may also emerge as an indirect effect of promoting individual-level change. Offord (2000) noted the possibility of achieving setting-level effects as a key advantage of universal interventions that target all individuals within a setting, and often these setting-level effects arise through social network dynamics. For example, social-emotional learning programs focus on individual-level skills (e.g., emotion knowledge and social problem-solving; Greenberg, Kusche, Cook & Quamma, 1995), but “a universal intervention intended to promote the development of social competence in all children should lead to an improved classroom atmosphere that supports improved interpersonal relations for all students” (CPPRG, 1999). Similarly, substance use prevention programs target individual-level skills (e.g., knowledge of consequences, anti-drug norms; Botvin & Griffin, 2004), but changes among many individual students in a school may produce synergistic benefits in the form of an environment with less risk of peer socialization toward substance use. In both examples, the “classroom atmosphere” or “peer socialization environment” improves partly due to the increased capacity of peers to provide each other with positive friendship support and from shifts in the social rewards and sanctions that peers provide to each other. These changes in relational supports and behavioral norms may translate into shifts in the behavioral bases of friendship formation, the distribution of social status, and the potential for positive and negative peer influence.

Our focus is on the value of social network analysis for conceptualizing and measuring these setting-level program effects. Attempts to conceptualize and measure setting-level processes are relatively new (Shinn & Yoshikawa, 2008). One traditional approach is to aggregate individual-level measures across all students within a setting: for example, school-level substance use norms can be defined by the average of the views expressed by the individual students at the school. Another approach is to rate the social setting based on direct observations, as when observers use a single numerical score to describe a classroom's “positive climate” (Pianta, La Paro & Hamre, 2007). These two approaches can provide useful information but they have important limitations: the first approach precludes consideration of social dynamics that are not reducible to an aggregation of individual characteristics or perceptions (Shinn & Rapkin, 2000; Tseng & Seidman, 2007) and the second approach cannot provide insight into the specific social dynamics underlying a global judgment. In this paper we propose concepts and measures from social network

analysis that are inherently setting-level in nature and that provide a systematic account of structural relationship dynamics.

Setting-level measures of social network dynamics are relevant to prevention science because of their potential to sharpen program theory and strengthen evaluation studies. Most broadly, network concepts and measures can strengthen program theory by contributing to the iterative process of intervention model building (Dishion & Patterson, 1999), facilitating the conceptualization and testing of progressively more fine-grained models of how an intervention affects social dynamics. Even when setting-level network dynamics are not the central target of an intervention, network dynamics may play a role as mediators of individual-level outcomes. For example, it is possible that social network dynamics account for the impact of family-based intervention programs on youth whose families did not participate in the intervention (Spoth, Redmond, Shin, & Azevedo, 2004). In cases where setting-level outcomes are the central interest (e.g., increased integration of special education students; Stevens & Slavin, 1995), network concepts and measures may strengthen evaluation studies by allowing program developers to conduct more precise and powerful tests of intervention effects.

Recent advances have brought network analysis to the forefront of fields ranging from physics to neuroscience to management (Barabási 2003; Watts 2003). Findings on the potential role of friendship networks in the spread of adult obesity and smoking cessation (Christakis & Fowler, 2007, 2008) have highlighted the need to develop intervention strategies that consider the relational context of individual health behaviors (Couzin, 2009). In prevention science, there has been substantial movement in this direction. For example, researchers have explored whether the network-informed selection of peer leaders enhances the impact of substance use prevention programs (Miller-Johnson & Costanzo, 2004; Valente, Hoffman, Ritt-Olson, Lichtman & Johnson, 2003), how networks of relationships among teachers influence the implementation of school reforms (Penuel, Frank & Krause, 2006) and how features of community coalition networks affect their operation (Feinberg, Riggs & Greenberg, 2005; Valente, Chou & Pentz, 2007). Network analytic methods hold great potential for advancing our understanding of the social processes involved in the diffusion of behaviors through social settings (Valente, 1995). These processes may be divided into those involving the structural features of the relationships among children and those involving dynamics linking network positions and affiliations with individual behaviors.

Prevention Efforts and the Structural Features of Peer Networks

Structural features of peer networks refer to the patterning of social ties among members of the network, without reference to individual member characteristics (e.g., attitudes or behaviors). In this section we focus on overall, setting-level patterns of social ties and review how patterns of social ties can also be used to define individual-level measures in the next section. School-based interventions may alter patterns of social ties in several different ways. Most broadly, however, many school-based interventions involve attempts to promote social integration in the classroom or school. Social network analysis can enable intervention researchers to conceptualize and measure these efforts with greater precision through its articulation of several interrelated but distinct facets of a network's level of social integration.

*Social integration*¹ refers to the overall richness and interconnectedness of *directional social ties* among members of a network. By *social tie*, we mean any type of relationship we may care to study between any two individuals in the network. Throughout this paper, we focus on the social tie of friendship because it is studied most frequently, but the social network framework applies equally well to other types of social ties (e.g., liking, disliking, seeking advice, social interaction). By *directional*, we draw attention to the difference between A naming B as a friend ($A \rightarrow B$) and B naming A as a friend ($B \rightarrow A$). Our first three indices of social integration describe the richness and interconnectedness of directional social ties. *Density* is the proportion of possible friendship ties (i.e., in a network with N members, $N(N-1)$ directional friendship ties are possible) that are made, capturing the volume of connections among youth. *Reciprocity* is the proportion of all friendship nominations that are reciprocated by the other party; and *transitivity* captures the extent to which “friends of friends are friends.”

The most socially integrated network would be one in which every individual names every other individual as a friend. In this situation, density, reciprocity and transitivity reach their theoretical maxima: in other words, it is not possible to increase the number of friendships in the setting, every single friendship nomination is reciprocated (for every $A \rightarrow B$, $B \rightarrow A$), and there is complete transitivity in friendship ties (for every $A \rightarrow B$ and $B \rightarrow C$, $A \rightarrow C$). Conversely, in a minimally integrated setting in which no one names any friends, the density of friendships is zero and reciprocity and transitivity have no obvious meaning and become undefined. These extreme cases underscore that the different facets of social integration are interrelated: as the number of friendships in a classroom increases, reciprocity and transitivity will increase. When the number of friendships in a setting is at intermediate levels, however, friendship patterns can vary widely and the different facets of social integration become uniquely informative. To illustrate, all of the networks in Figure 1 have the same density ($6/30 = .20$), but reciprocity increases from .00 in *1a* to 1.00 in *1b* and *1c*; and transitivity increases from .00 in *1a* and *1b* to 1.00 in *1c*.

Where these first three indices of integration characterize the larger network through a simple aggregation of information about pairs or triads of individuals, three additional indices capture the broader pattern of social ties across all members of the network. First, networks vary in the extent to which there is a social hierarchy. In a strongly hierarchical setting, a small number of individuals receive most of the friendship nominations while others receive few or none; whereas in a more egalitarian setting, friendship nominations are more evenly distributed. Hierarchy can vary markedly even when other indices of social integration remain similar. In Figure 2, for example, density remains constant but hierarchy is greater in *2a* than in *2b*. Hierarchy is typically calculated as a centralization index (Wasserman & Faust, 1994), which reaches a theoretical maximum of 1.0 when a single individual receives all of the nominations and a theoretical minimum of zero when all individuals receive the same number of nominations. Centralization can be computed for any of the several individual-level indices of network centrality described below.

Second, social networks vary in the degree to which they can be divided into distinctive subgroups. Highly distinctive subgroups indicate a relatively poorly integrated setting whereas less distinctive subgroups suggest a more integrated setting. An intuitive index of subgroup distinctiveness is the relative density ratio, calculated as the density of within-group ties divided by the density of between-group ties, where subgroups could be defined by any social category of interest (e.g., race/ethnicity, educational classification). In Figure 3, the density of within-group ties in Fig3a is .75 (30 of 40 possible directional friendship

¹In the sociological literature, social integration refers to the degree to which minority groups are integrated into the mainstream, but here we use the term more broadly to refer to the connectedness of a group of individuals without regard to their minority group status.

ties exist) and the density of between-group ties is .06 (3 of 50 possible friendship ties exist), producing a relative density ratio of 12.5 ($.75/.06 = 12.5$). In Fig 3b, three additional between-group ties are added, which increases between-group density ($6/50 = .12$) and decreases the relative density ratio to 6.125 ($.75/.12 = 6.125$). In both networks, within-group friendships are far more likely than between-group friendships, but this segregation is less extreme in network 4b. The intuitive notion of relative density ratio underlies various measures of *modularity* that are being used increasingly to quantify the degree of “groupness” in a wide range of networks (Girvan & Newman, 2002; Porter, Onnela & Mucha, 2009).

Finally, Moody and White (2003) introduced a measure of structural cohesion that is anchored in the more formal properties of graph theory (a mathematical framework for characterizing networks), capturing the extent to which a network is prevented from splitting into distinct and unrelated subgroups by few versus many individuals whose friendship ties connect the subgroups (weak vs. strong cohesion). Structural cohesion depends on the entire pattern of social ties across all members of the network. In that sense it more broadly reflects how strongly all members are linked to each other through multiple indirect paths of “friends of friends.”

Awareness of these distinct conceptions and corresponding measures of social integration can foster greater specificity in prevention program theories and more sensitive measures of program impact. For example, universal social-emotional learning interventions that promote the ability to initiate and maintain positive relationships (Greenberg et al., 1995; Botvin & Griffin, 2004; Hansen & Dusenbury, 2004) may aim to increase the density and reciprocity of friendships in a classroom. Efforts to reduce subgroup distinctiveness may take the form of small group learning interventions that foster social ties between traditionally segregated factions of a classroom, such as students belonging to different racial groups (Aronson, Blaney, Stephin, Sikes & Snapp, 1978) or different academic tracks (Cohen & Lotan, 1995), or cooperative learning interventions promoting the integration of previously marginalized groups (Stevens & Slavin, 1995). Efforts to reduce extreme disparities in peer acceptance or peer rejection (Farmer, 2000) may be conceptualized as efforts to reduce the centralization of status in the network.

In sum, consideration of different structural features of social networks may stimulate more refined theories specifying the intended effects of an intervention, and social network analysis offers well defined indices that may provide more sensitive measures of whether these intended effects are achieved. Network indices can also reveal unintended effects or tradeoffs in effects on different facets of social integration (e.g., increasing friendship density may inadvertently increase subgroup distinctiveness or increase status hierarchies). In either case, an important feature of the indices described above (summarized in Table 1) is that they are based solely on the patterning of social ties among individuals in the setting. Thus they are truly setting level phenomena, not redundant with effects on the specific attitudes or behaviors targeted by an intervention. Next, we consider additional concepts and measures from social network analysis that summarize patterns of social ties in relation to the distribution of individual attributes, such as demographic characteristics, attitudes or behaviors.

Prevention Efforts and the Behavioral Dynamics of Peer Networks

Where the structural features we just discussed concern only the pattern of social ties among network members, behavioral dynamics also concern individuals' attributes, such as their attitudes, values and behavior. Behavioral dynamics capture the potential for peer influence in a setting. Social network analysis views interpersonal influence as a diffusion process in

which attitudes, values, and behavior spread among actors via the linkages that form the network. When transmitted through a network of interdependent friendship linkages, dyadic processes produce both ongoing mutual influence between friends and diffusion of influence received from one friend outward toward other friends, and in turn their friends, and so on. Accordingly, the friendship network specifies how each person both receives and transmits a complex pattern of direct and indirect influences. Whether influence promotes individual stability or change in attitudes and behavior depends on the similarity versus difference between the parties involved, in combination with the pattern of connections among them. This general framework for considering behavioral dynamics in networks can accommodate diverse specific influence processes, such as information flow, the coercion of unpopular youth by popular peers, or influence driven by the average or variance characteristics of one's friends.

More specifically, the behavioral dynamics of peer networks refer to the distribution of individual attitudes or behaviors across the network, and the salience of these individual attributes as youth choose their friends (peer selection) and are influenced by these friends (peer influence). As with our discussion of structural features of networks, we focus mostly on setting-level measures, but sometimes we use individual-level measures of social position to define setting-level features. Interventions attempt to alter the behavioral dynamics of peer networks in multiple ways. From a competence-promotion perspective, interventions may attempt to increase the base rates of desired individual attributes (e.g., prosocial behavior), elevate the social position of individuals with these attributes and increase their influence over others. From a risk-reduction perspective, interventions may seek to reduce the base rate of undesired attributes (e.g., substance use) or decrease the social influence of individuals with these attributes (e.g., by changing the persuasion process by which they influence peers). Several concepts and measures from social network analysis can clarify these behavioral dynamics.

As with the discussion of structural features of networks, it helps to begin by developing some intuitive notions in the context of extreme examples. Note that we generally expect influence to flow in the opposite direction of the arrows illustrating friendship choices: when A names B as a friend, but B does not choose A ($A \rightarrow B$), B is thought to be in a position of influence over A because B is part of A's reference group (i.e., the group A uses to evaluate her own attitudes or behavior; Merton & Kitt 1950; Newcomb 1950). In Figure 4a, one individual displays the "problem behavior", but no one selects this individual as a friend, suggesting that she is not in a position to influence others; and she has both direct and indirect positive influences (i.e., friends and friends-of-friends who do not display problem behavior). Over time, we might expect this individual's problem behavior to be replaced by positive behavior. In contrast, in Figure 4b, the individual displaying problem behavior is in a position of potential influence with respect to all other members of the network, suggesting that the problem behavior may become valued in the network and "diffuse" or spread over time. Finally, Figure 4c illustrates a setting in which there is a high base rate of the problem behavior, compounded by the fact that youth who engage in problem behavior comprise the entire reference group of the youth who does not. Over time, one might expect the problem behavior to spread to this individual, and perhaps eventually to all other non-problem youth through a similar influence process. Note that there is some uncertainty regarding the outcome of influence processes in 4b and 4c because several youth have friends characterized by a mix of problem and non-problem behavior. This is typical of the complexity of peer influence dynamics in real social networks.

These examples illustrate that peer networks may play a role in behavioral development through multiple processes, each of which is a potential target of intervention efforts. Most directly, an intervention could slow the diffusion of problem behavior through a peer

network by decreasing (or slowing the growth in) the *base rate of a problem behavior*: given a specific network of friendships, a lower base rate of problem behavior means there are fewer pathways along which the problem behavior could diffuse. It would be problematic to study this component as a setting-level phenomenon, however, because the rate of problem behavior is the simple aggregate of the individual outcome that the intervention targets: treating it as a direct source of influence risks the tautology of concluding that “the intervention reduced average levels of problem behavior by reducing individual levels of problem behavior.” Our discussion therefore focuses on three aspects of the influence process that more meaningfully demonstrate the added value of a network perspective. Two of these processes involve *peer selection* dynamics: an intervention could decrease the tendency to choose peers who engage in problem behaviors as friends, implying a shift in behavioral norms (Henry et al., 2000); or it could change the degree to which youth form friendships with peers who are similar to themselves on levels of the problem behavior. A third process involves *peer influence* dynamics: an intervention could make students more resistant to the influence of students who engage in problem behaviors.

Peer selection: behavioral norms

The social norms favoring a behavior can be inferred from the frequency with which individuals displaying that behavior are selected as friends. When social norms support a behavior, individuals displaying that behavior should be named as friends frequently and occupy central positions in the network; when social norms oppose the behavior, individuals displaying the behavior should be named as friends less often and occupy peripheral positions in the network. It follows that, if one can obtain measures of individual behavior and measures of “centrality” for each individual in the social network, then the correlation between those two variables can serve as an index of setting-level behavioral norms (“salience norms”; Cialdini, Kallgren & Reno, 1991). A positive correlation would reflect social norms favoring the behavior (Alexander, Piazza, Mekos & Valente, 2001), and a negative correlation would reflect norms opposing the behavior. Thus, for example, a drug abuse prevention program might aim to alter the correlation between network centrality and attitudes favoring drug use to become less positive or more negative.

Network centrality, the extent to which one is at the “center” of the network, is a core concept for characterizing an individual’s structural position and potential for influence in a network (Freeman 1979; Wasserman & Faust 1994). Several different measures of potential for influence have proved relevant for studies of problem behavior (Bearman & Moody 2004; Ennett & Bauman 1993; Haynie 2001), and although these indices tend to be moderately intercorrelated (Valente et al, 2008), each emphasizes a somewhat different aspect of what it means to be in a position of potential influence within a network. The most familiar metric to developmental researchers, and the one we used in the examples above, is *in-degree centrality*. Also called *popularity* by network researchers, in-degree centrality is simply the total number of directed ties received by an individual (in this case, friendship nominations). Individuals who are named as a friend by many peers are in a position to influence more people than individuals who are named as a friend by only a few peers. A related index, *eigenvector centrality*, takes into account both the individual’s in-degree centrality and the in-degree centrality of the peers who name the individual as a friend. This recognizes the added influence that may derive from being named as a friend by peers who are themselves a reference group member for many others in the network. Alternatively, *betweenness centrality* emphasizes the degree to which an individual links distinct sub-sets of the network by having ties with people who are not otherwise connected to each other. Individuals with high betweenness centrality are important because they can communicate quickly to different types of people (Burt, 1992). For example, in network 4a above, the individuals involved in the between-group friendships would have relatively high

betweenness centrality. The broader point here is that multiple indices of individual network centrality beyond “in-degree” exist and can be related to measures of individual behavior to provide conceptually grounded and efficient summaries of setting-level behavioral norms.

Behavioral norms involved in friendship selection are a major focus of prevention programs. For example, both All Stars and Project Alert focus intensively on altering social norms by motivating students against drug use, establishing new attitudes and beliefs opposing use and addressing peer norms (Ellickson, Miller, Robyn, Wildflower & Zellman, 2000; Hansen & Dusenbury, 2004). In addition, both of these programs and school-based (Botvin & Griffin, 2004) and family-based programs (Molgaard, Kumpfer & Fleming, 1997) contain lessons emphasizing the importance of selecting friends who help youth achieve prosocial goals, and the disadvantages of selecting friends who engage in problem behavior. From a network perspective, if these programs are effective one should expect students exhibiting pro-use attitudes or behaviors to occupy less central positions within the network over time.

Peer selection: behavioral similarity

A distinct aspect of the peer selection process is the degree to which individuals choose friends who are similar to themselves with regard to a specific behavior. Traditionally this tendency is quantified by correlating the individual’s score on the behavior to the average score of the individual’s friends, but a more network-sensitive approach is to compute a spatial correlation that relates behavioral differences between friends to the geodesic distances between them (Doreian 1981, 1990). A strong correlation suggests that friendship networks are organized around the behavior. It is not clear whether interventions should aim to increase or decrease in the tendency to select friends based on a specific problem behavior. A drug-use prevention program might aim to reduce the degree to which drug-using youth seek each other out (reducing selection-driven similarity), but to the extent that behavioral norms shift strongly against drug-use, these youth may have fewer social options and thus may seek each other out to an even greater degree (increasing selection-driven similarity). In contrast, in a setting in which youth displaying aggression or attention problems are rejected by more prosocial peers (Dishion & Patterson, 1999), interventions may seek to promote these youths’ friendships with prosocial peers, thereby reducing selection due to similarity on aggression and attention problems (Mikami, Boucher & Humphreys, 2005). Here social network thinking points us to an unanswered question of central importance to program strategy.

Peer influence processes

Peer influence on a behavior exists to the degree that individuals change their behavior in the direction of becoming more like their friends. Even in two networks with identical distributions of relationships and behaviors, there may be differences in the degree to which a behavior diffuses through the network due to differences in the strength of interpersonal influence processes. Specifically, the content, quantity and impact of processes of evaluative feedback, persuasion, coercion, resource control and reinforcement may differ across networks (Dishion, Andrews, & Crosby, 1995; Hawley, Little, & Pasupathi, 2002; Sage & Kindermann, 1999).

Many prevention programs seek to support the diffusion of desired behaviors and suppress the diffusion of undesired behaviors. For example, teaching young children to compliment each other for positive behavior can be seen as an effort to increase social reinforcement processes that will increase the diffusion of positive behaviors through the peer network (Greenberg et al., 1995). Substance use prevention programs invest a substantial portion of their lesson content in attempts to alter peer influence dynamics involving interpersonal processes of persuasion and coercion. They try to enhance the transmission of anti-drug

attitudes by encouraging youth to serve as positive role models for their peers and to help them resist drug use. For example, the Iowa Strengthening Families Program includes activities and discussions to help youth learn how to discourage or counsel their friends away from high-risk situations (Molgaard et al., 1997). These programs also try to decrease the diffusion of pro-drug attitudes and behaviors by building resistance or refusal skills. For example, Project Alert (Ellickson et al., 2000) devotes four of its eleven lessons to practicing diverse ways to resist peer pressure. From a network perspective, such efforts could have an important effect on patterns of behavior diffusion over time. For example, even if an intervention had no initial impact on rates of drug use or on friendship patterns, it could affect longer-term patterns of drug use if non-users exerted more positive behavioral influence over their friends or if they became less susceptible to the influence from friends who used drugs.

Structural and behavioral dynamics of peer networks: Implications for prevention science

Sharpening prevention program theories

Many prevention programs share the broad goal of enhancing children's social relationships and behavior in school settings. A network perspective can be helpful in formulating more precise statements about the features of peer social networks that are targeted by different interventions, or by the different components of a single intervention. A key distinction is between interventions targeting structural features of social networks and interventions targeting behavioral dynamics.

Interventions that aim to enhance levels of social integration in a setting are focused on one or more structural features of the network. Most broadly, interventions may seek to increase the establishment and maintenance of friendships in the setting, which may be manifest in measures of friendship density, reciprocity and transitivity. Interventions with this goal are typically universal in nature, involving either the reconfiguration of the social setting (Felner et al., 1993) or the universal promotion of social skills to support friendship formation and maintenance. Interventions may also seek to promote social integration by decreasing the segregation of students belonging to traditionally separate social groups (Aronson et al., 1978; Cohen & Laton, 1995), evidenced by a change in the relative density ratio of within-group to between-group friendships. Finally, interventions may enhance social integration by helping socially peripheral youth develop new social ties, thereby reducing the hierarchical nature of the setting (i.e., the degree to which friendship nominations are centralized among only a few youth).

We have focused on friendships for purposes of illustration, but program theory may direct attention to other types of social ties. Interventions concerned with status hierarchies may focus on patterns of peer acceptance and rejection (i.e., nominations as "liked most" and "liked least"). Substance use prevention programs guided by social reference group theory may find it more meaningful to ask youth to nominate whom they "want to be like," "look up to," or "who influences you." The broader point is that social status in schools is a multidimensional construct (Rodkin, Farmer, Pearl & Van Acker, 2006), and the type of tie that should be studied should be guided by both developmental theory regarding the key process of peer influence and program theory regarding the process of change promoted by intervention activities.

Interventions that focus on the behavioral dynamics of peer networks may aim to alter behavioral norms, change the degree to which the social network is organized around the behavior, or change peer influence dynamics. The combination of high levels of both selection and influence for a problem behavior is of special concern to prevention

researchers because it implies a feedback cycle producing exceptionally high levels of problem behavior in a portion of a student population. Consequently, most prevention efforts concerned with behavioral dynamics attempt to reduce selection for problem behavior (or increase selection for desired behavior) and reduce the influence of peers displaying this behavior (or increase the influence of youth displaying desired behavior).

A network perspective has value in part because it offers a way of distinguishing among these many potential setting-level targets of prevention efforts. But a program theory is most useful when it becomes part of an inductive-deductive process of inquiry in which limitations in developmental or program theory are revealed and subsequently modified (Dishion & Patterson, 1999). Recent advances in methods for network analysis facilitate this process.

Strengthening program evaluation

The last decade has brought rapid advances in the development of integrative network analytic methods and in relatively accessible software to implement them. Good resources are readily available for the measurement of structural features of social networks. Free or inexpensive software is available to compute all of the structural indices described above, plus many more (Borgatti, Everett & Freeman, 2002; Handcock, Hunter, Butts, Goodreau & Morris, 2003; Huisman, M., van Duijn, M. A. J., 2005; Moody, 1999). Free programs are also available to visualize static or dynamic networks (Bender-DeMoll, Moody & McFarland, 2006; Borgatti, 2009; de Nooy, Mrvar & Batagelj, 2005).

Analytic strategies for describing behavioral dynamics of social networks present many challenges, but new solutions are emerging (Snijders et al., 2007) and being applied in developmental studies of youth in school settings (Hanish & Rodkin, 2007). Traditional approaches to testing for peer selection and influence dynamics begin with the computation of a score for each individual that represents the average score of the individual's friends on a behavior or attitude of interest. These scores are then entered into linear regression models to detect selection effects (i.e., does the individual's score predict the average score of new-friends?) or influence effects (i.e., does the average-peer score predict changes over time in the youth's score?). This approach has produced useful insights but it violates the assumption of independent observations because most individuals are involved in multiple friendships and thus contribute to the "average-peer" score of many peers. Furthermore, the similarity between mutual friends is implicitly double-counted as influence (or selection) in both directions. Restricting analyses to a subset of the social ties in a network (e.g., identifying a set of dyads such that each individual is only represented in one dyad) meets formal statistical assumptions of independent observations, but it involves discarding the majority of data on dyadic relationships and removes triad-level and larger network dynamics from view, ignoring the considerable evidence that these dynamics play a key role in network dynamics (Snijders et al., 2007).

New analytic strategies that model the dependencies in social network data are emerging. Network diffusion models provide a formal representation of both selection and influence processes in social networks (Friedkin 1998; Snijders et al., 2007). These methods offer an important advance over standard individual level analyses because they take into account the interdependencies inherent in network data and estimate reciprocal and indirect influences, as well as direct influences. Friedkin's (1998) diffusion model can be implemented with modules in SAS (Moody, 2000); and Snijders' actor-based extension of this approach to multi-wave longitudinal data can be implemented in his free SIENA package (Snijders et al., 2007).

School-based intervention researchers are centrally concerned with setting-level social dynamics. Many programs focus intervention activities at the individual-level with the goal of producing setting-level effects (Offord, 2000). Numerous others make explicit and direct attempts to affect setting-level social network dynamics by changing the organizational or instructional systems that channel and constrain children's relationships with each other (Aronson et al., 1978; Battistich et al., 2000; Felner, et al., 2000); or by altering behavioral norms or selection and influence dynamics (Botvin & Griffin, 2004; Ellickson et al., 2000; Molgaard et al., 1997). However, the central role of peer network dynamics is typically implicit rather than explicit in these programs, and evaluation methods typically reduce implied network dynamics to an aggregation of individual characteristic (Tseng & Seidman, 2007) or use methods that do not account for the interdependencies of network data. We believe that integrating concepts and analytic methods from network analysis into prevention science has great potential as an important new avenue for refining program theories and providing more focused tests of intervention effects. Progress in such an integration of network concepts and prevention science also has the potential to inform discussions (Couzin, 2009) of the implications of social network analysis for the broader realm of public health efforts.

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Figure 1.

These three figures represent groups of six individuals characterized by identical network density but different patterns of reciprocity and transitivity: (1a) no nominations are reciprocal or transitive; (1b) all nominations are reciprocated but none are transitive; (1c) all nominations are reciprocated and transitive.

Figure 2.

These figures illustrate networks comprised of six individuals with identical network density but different degrees of hierarchy. The strong hierarchy in network 2a, in which two individuals receive all of the nominations, is evident in the wide variation in the total number of friendship nominations received (clockwise from top: 0,4,0,0,4,0). Hierarchy is less prominent in network 2b, where the distribution of total nominations received is more evenly distributed (1,2,2,0,2,1).

3a

3b

Figure 3.

These networks illustrate settings in which groups vary in their distinctiveness. In both networks, the two groups have the same pattern of dense within-group friendships. In network 3a, the groups are relatively distinct from each other, with only one reciprocated friendship and one unreciprocated friendship connecting them. The groups in network 3b are somewhat less distinct due to the addition of another reciprocated friendship and another unreciprocated friendship. This change can be quantified as the relative density of within-group and between-group ties (relative density ratio).

Figure 4.

These networks demonstrate different potential for the diffusion of problem behavior from youth who already display it (red nodes with “-”) to other youth (blue nodes with “+”). In network 4a, there is little potential for the diffusion of problem behavior because the youth with problem behavior is not in a position to influence others and is subject to direct and indirect positive influences. Network 4b presents a mixed picture: diffusion is possible because all four non-problem youth look to the problem-behavior youth as a friend, but the problem-behavior looks to two non-problem youth as friends. In contrast, network 4c appears primed for the diffusion of problem behavior because one of the non-problem youth look to each other for friendship and appear to be in positions of direct or in-direct influence over the non-problem youth.

Table 1

Summary of Social Network Indices

Index	Definition	Computation and Software Resources
<i>Social Integration (setting-level)</i>		
Density	The proportion of possible friendship ties that are present	<i>Computation:</i> In a network with N members, the number of directed ties divided by $N*(N-1)$. (W & F, p. 164) <i>Software:</i> UCINET Network>Cohesion>Density>Density_Overall
Reciprocity	The tendency for directed friendship ties to be reciprocated	<i>Computation:</i> The number of reciprocated ties divided by the total number of directed ties (W & F, p. 165) <i>Software:</i> UCINET Network>Cohesion>Reciprocity
Transitivity	The extent to which “friends of friends are friends”	<i>Computation:</i> The proportion of times in which, when A names B and B names C, A names C (i.e., for all $A \rightarrow B$ and $B \rightarrow C$, in what proportion $A \rightarrow C$?) (W & F, p. 165) <i>Software:</i> UCINET Network>Cohesion>Transitivity (Type=Adjacency)
Network centralization	The extent to which friendship nominations are unevenly distributed in the network, suggesting a hierarchy	<i>Computation:</i> Centralization quantifies the degree of spread or dispersion in the centrality scores of actors in a network, and is scaled so that it is zero when all individuals have the same centrality score and 1 when one individual receives all of the friendship nominations in the network (W & F, pp. 176-177) <i>Software:</i> UCINET Network>Centrality>Degree
Relative density ratio	The extent to which friendship ties tend to exist within rather than between social subgroups	<i>Computation:</i> The ratio of the density of within-group ties to the density of between-groups ties <i>Software:</i> UCINET Network>Cohesion>Density>Density_by_Groups
Modularity	The extent to which friendship ties tend to exist within rather than between social subgroups, but taking into account the chance likelihood of between-group ties given each individual's number of ties.	<i>Computation:</i> The proportion of friendship ties that fall within social subgroups minus the proportion of such ties expected by chance given the in-degree of each individual (Newman & Girvan, 2004) <i>Software:</i> SPAN 3.0 SAS modules (Moody, 1999)
Structural cohesion	The extent to which a network is prevented from splitting into distinct and unrelated subgroups by few individuals (weak cohesion) versus many individuals (strong cohesion) whose friendship ties connect the subgroups	<i>Computation:</i> “A group's structural cohesion is equal to the minimum number of actors who, if removed from the group, would disconnect the group” (Moody & White, 2003; pp. 108) <i>Software:</i> SPAN 3.0 SAS modules (Moody, 1999); also the R
<i>Potential for behavioral influence (individual-level)</i>		
In-degree centrality	The number of network members who nominate an individual as a friend.	<i>Computation:</i> The total number of directed friendship nominations received (W & F, p. 178) <i>Software:</i> UCINET Network>Centrality>Degree
Eigenvector centrality	Similar to in-degree centrality, but takes into account the in-degree centrality of the peers who name the individual as a friend (i.e., higher eigenvector centrality for those who are named as friends by peers with high in-degree centrality).	<i>Computation:</i> Each individual's eigenvector centrality is defined by the individual's loading on the principal eigenvector of the adjacency matrix defining the network (Borgatti, 2005, p. 61) <i>Software:</i> UCINET Network>Centrality>Eigenvector
Betweenness centrality	The degree to which an individual links	<i>Computation:</i> An individual's betweenness centrality is based on the number of “shortest paths” (geodesics) between members of the network that pass through

Index	Definition	Computation and Software Resources
	distinct sub-sets of the network by having ties with people who are not otherwise connected to each other	that individual (W & F, p. 190) <i>Software:</i> UCINET <i>Network>Centrality>Freeman_Betweenness>Node_Betweenness</i>

Note: W & F refers to Wasserman & Faust (1994).