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NETWORK STRUCTURAL INFLUENCES ON THE ADOPTION OF EVIDENCE-BASED PREVENTION IN COMMUNITIES

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Abstract

This study examined the impact of key variables in coalition communication networks, centralization and density, on the adoption of evidence-based substance abuse prevention. Data were drawn from a network survey and a corresponding community leader survey that measured leader attitudes and practices toward substance abuse prevention programs. Two types of coalition networks were measured: advice-seeking and discussion relations. For each community, we computed network-level measurements ($n = 20$), and then used multiple linear regression. Results showed that adoption outcomes were associated with a decrease in centralization for the advice network and an increase in centralization for the discussion network, controlling for density. This suggests that community coalitions might consider decreasing their network density in such a manner that distributes power and influence among a broader base of coalition members to seek advice about programs while simultaneously discussing these programs in a more concentrated group to facilitate decisions about which programs to adopt.

Public health research has increasingly focused on the use of community-based approaches to promote and disseminate evidence-based health practices and prevention programs (see IOM, 2003), and on the potential of community coalitions to move adoption of evidence-based prevention and public health programs forward. Generally defined, a community coalition is an organization of individuals or groups that represent diverse interests and whose members agree to work together to achieve a common goal, in this case, promoting evidence-based prevention practices and programs in a community (Wandersman et al., 1996). Coalitions enable greater access to and sharing of resources than might otherwise occur with single individuals or groups, and are considered useful vehicles for building community capacity in general¹ (Butterfoss & Kegler, 2002; Chaskin, 2001; Crisp, Swerissen, & Duckett, 2000; Kadushin, Lindholm, Ryan, Brodsky, & Saxe, 2005; Singer & Kegler, 2004).

A number of studies have suggested coalition factors that are associated with community capacity to implement public health initiatives. One indicator of community capacity is

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¹Community capacity refers to the ability of a community to organize itself to identify, mobilize and address social and health problems (Goodman et al., 1998).

positive coalition functioning, which has been associated with formalization, leadership style, membership participation/diversity, agency collaboration, group cohesion, and positive communication among coalition members (Riggs, Nakawatase, & Pentz, 2008; Zakocs & Edwards, 2006). However, underlying coalition functioning may be a coalition's ability to network, which facilitates communication and collective problem solving (Goodman et al., 1998; Kadushin et al., 2005; Kreuter & Lezin, 2002; Norton, McLeroy, Burdine, Felix, & Dorsey, 2002).

COMMUNITY COALITION NETWORKS

Researchers are increasingly applying social network analysis to the understanding of how coalitions function best in promoting health and prevention initiatives in communities (Feinberg, Riggs, & Greenberg, 2005; Kwait, Valente, & Celentano, 2001; Luke & Harris, 2007). Network studies of community coalitions emphasize the structural dimension of community capacity in community-based intervention (Kegler, Steckler, McLeroy, & Malek, 1998; Provan, Nakama, Veazie, Teufel-Shone, & Huddleston, 2003; Provan, Veazie, Teufel-Shone, & Huddleston, 2004; Singer & Kegler, 2004; Valente, Chou, & Pentz, 2007), and examine patterns of effective collaborative organizational networks. Network analysis normally generates several specific indicators of community coalition communication patterns. For example, previous studies have shown that network properties of density and reciprocity, as well as the interaction characteristics of frequency and intensity, are positively associated with networks ability to enhance community capacity (Goodman et al., 1998; Kegler et al, 1998; Provan et al., 2003; Provan et al, 2004; Singer & Kegler, 2004). Cohesive interorganizational networks are characterized by reciprocal links, frequent supportive interactions, and having overlap with other networks within a community (Goodman et al., 1998). These structural properties are important in enhancing community capacity, enabling communities to address health issues more efficiently through organizational collaboration.

In a study of the dynamics of coalition networks in community health, the density of collaborative network relationships increased over time in both frequency and strength, which indicates the effectiveness of attempts to build community capacity (Provan et al., 2003). This indicates that cohesive coalition networks lead to increased network effectiveness by facilitating communication.

Conversely, Valente and colleagues (2007) found a negative relationship between network density and performance, suggesting that increased communication among coalition members was associated with decreased adoption of evidence-based intervention programs. They hypothesized that overly dense networks can create communities with too few connections to external information and resources beyond their own strongly connected groups, indicating that less dense communities tend to be better at adopting evidence-based practices because their "weak ties" to other organizations provide access to additional resources and power.

Such an argument is consistent with Granovetter's strength of the weak ties theory, where weak ties are defined as those ties between-group members, rather than strong, or in-group ties; weak ties provide people with access to information and resources beyond those

available in their own social circle through bridging cliques bound together by strong ties (Granovetter, 1973, 1983). In this sense, the weak ties, more commonly present in less-dense networks, enable connections to organizations not otherwise accessible when core community ties are too strong (Granovetter, 1995). These connections are also integral to community mobilization. The present study refers to density as the degree to which communication networks are accessible to external information and resources, and the expectation that sparser coalition networks provide more access to external information and resources, facilitating greater information exchange and thus diffusion of prevention programs.

COMMUNITY COALITION AS A SYSTEM

The concept of weak ties in communication networks raises the question of whether a coalition can be considered an operating system, rather than just a structure for promoting prevention in a community (Hawkins, Catalano, & Arthur, 2002). In that case, network changes in density and centralization (as well as other indicators potentially) might be expected to work in concert. This view is somewhat supported by collective action theory. Collective action theory documents the social network influence of the prospect of collective mobilization and thus may aid in identifying other characteristics of a coalition that help mobilize participation of community members in health promotion coalitions. Such participation is believed to increase the likelihood of program success (Butterfoss, Goodman, & Wandersman, 1996).

Sociological research on collective action demonstrates the significance of density and centralization in social networks to collective action (Chwe, 1999; Gould, 1993; Kim & Bearman, 1997; Marwell, Oliver, & Pahl, 1988; Oliver, Marwell, & Teixeira, 1985). For instance, Marwell and colleagues (1988) report the positive effect of a network's centralization on collective action controlling for network density, which indicates that the same number of ties are more effectively employed if they are centralized. On the other hand, there was no difference in the level of coalition activities between environmental movement organizations that use centralized and decentralized decision-making styles (Shaffer, 2000).

Diffusion of innovation study theorizes that a highly centralized network, due to hubs that serve as dissemination portals to other members in the network, often has faster diffusion of innovation (Valente, 1995, 2005). In such networks, actors who have a structural position of power and control (Freeman, 1979) can enact decisions more readily. Valente and colleagues (2007) indicate that this is the double-edged sword of centralized networks. Centralized networks are expected to facilitate the adoption of an evidence-based program, but an overcentralized network leads to a decisionmaking process that does not easily allow for all members to participate. Therefore, this results in a lower commitment to prevention programs among noncentral members. Because collaborative leadership and new leadership opportunities through civic leadership roles (Kegler, Norton, & Aronson, 2008) contribute to fostering the organizational/community capacity of the community-based coalitions, a decentralized network might better facilitate adoption of new programs. With respect to community readiness, empirical findings also imply that community coalitions with less-

centralized networks may be better at implementing a community-based prevention initiative (Feinberg et al., 2005).

What is missing in network studies on community coalitions is an analysis of the combined progressive influence of network density and network centralization on coalition effectiveness. In social network theory, the concepts of density and centralization describe distinct aspects of the overall structure of a network. Density describes the level of cohesion, and centralization the extent to which this cohesion is organized around its most central points (Scott, 2000). By treating these network indices as simultaneous effects that represent a coalition operating as a system to promote prevention, we expect that network density and centralization will affect each other before they affect prevention outcomes.

The present study investigates the combined effect of changes in density and centralization on the outcomes representing adoption of evidence-based substance abuse prevention programs using longitudinal coalition data. Prior coalition network study reported that decreased density was associated with improved adoption (Valente et al., 2007). Our study extends this finding to address the question of how a decrease in density accompanied by changes in centralization also affects the functioning of coalition networks.

However, there is relatively little information on whether the functional network that community leaders rely on is associated with successful organizational outcomes for prevention. Conventional network literature in the diffusion of innovation among physicians suggests that individuals engage in at least three types of functional networks based on advice (instrumental and action needs), discussion (trusted close colleagues), and friendship (affective) (Burt, 1987; Coleman, Katz, & Menzel, 1957, 1966), and effectiveness of these networks at each stage of the diffusion process. Coleman and colleagues report that adoption of a new drug diffused through the communities of physicians in distinct stages; first influence of social network operated through professional relations (i.e., advisors or as discussion partners), and then through friendship relations (Coleman et al., 1957, 1966). Based on these findings, the present study analyzes data on professional relations among coalition member (i.e., both advice-seeking and discussion networks) because our study is based on the earlier stage of development in the coalition through intervention (the first 18 months). We assume that both types of networks were assumed to operate in community coalition communications and facilitate prevention outcomes.

It must be noted that both advice and discussion relations may generate distinct network dynamics driven by a different operationalization of centralization. Our study operationalizes network centralization based on degree centrality (Freeman, 1979). Degree centrality measures the extent that actors connect to other actors through direct ties. For networks with directed relations (asymmetric networks), we can separate directionality of direct ties into indegree (receiving ties) and outdegree (sending ties). An actor with high indegree centrality (i.e., many others in a network have direct ties to him or her) is more likely to be acknowledged by others in the network, indicated by having a high prestige. An actor with high outdegree centrality (many others in a network have direct ties from him or her) is more likely to recognize others, and this indicates being influential in a network (Freeman, 1979).

In advice networks, we operationalize centralization differently from the prior study conducted by Valente and colleagues (Valente et al., 2007) where centralized networks were implicitly defined by containing fewer, prestigious leaders whom others sought for advice (i.e., indegree), indicating their prominence in a network (Hanneman, 2005). The Valente and colleagues (2007) study did not find a significant effect of centralization on adoption outcome. We assume that the leaders who are considered prestigious by other members might also be those who are senders of information rather than receivers (Wasserman & Faust, 1994). Thus, we conceptualize centralized advice networks as those composed of the few leaders who seek advice from many others, and hence operationalize the centralization based on outdegree centrality. Such leaders (i.e., having a high outdegree) are then able to gather information and pass it on to others, while making others aware of their views and thus also exert their influence on the network (Hanneman, 2005). As for the discussion network, we conceptualize centralized networks as those composed of few prominent leaders who are in charge of deciding how they will implement measures to achieve adoption. These leaders are likely to be acknowledged as such through discussion by others. Thus, we operationalize network centralization based on indegree centrality for discussion network.

In sum, this study tests two hypotheses: (a) As outdegree centralization decreases (i.e., decreasing concentration of influential leaders), coalitions have better adoption outcomes for the advice network; and (b) as indegree centralization increases (i.e., increasing concentration of prominent leaders), coalitions have better adoption outcomes for the discussion network. Both hypotheses are based on a controlled density level that is expected to decrease over time, which should generate better adoption outcomes. In this way, we assume a progressive relationship with respect to how a coalition best proceeds in making decisions related to integrating evidence-based prevention into its community.

DATA AND METHOD

The study is part of a large prevention diffusion trial called Steps Toward Effective Prevention (STEP). The STEP trial evaluated the dissemination of evidence-based drug prevention programs² in 24 cities and included a community coalition intervention component (Pentz, 2003, 2004). Small- to medium-size cities (populations = 20,000–104,000) were recruited from Massachusetts, Colorado, Arkansas, Iowa, and Missouri to participate in a 5-year randomized trial. The selected cities were considered underserved with regard to drug prevention (i.e., few funds for prevention, no state incentive grants, and no evidence-based programs). The STEP program used relatively low-cost interactive up-and-down-link satellite television training to deliver six evidence-based prevention programs over a 3-year period. At baseline, 67% of the cities reported having an existing coalition that ranged in longevity from 2 to 25 years, 21% had created a prevention coalition specifically for STEP, and 12% had an informal group of community leaders who met for prevention planning.

²Evidence-based programs are those that have been systematically evaluated and shown to be effective in changing health-related behavior (Valente et al., 2007). Drug abuse prevention is known as well articulated in such programs (Pentz, 2003, Center for substance, 2002).

Research and Measurement Designs

Cities were matched with 2000 U.S. Census data on demographic variables associated with risk for drug use (percentage of the population that was male, younger than 18 years, White, or had income below the federal poverty level). Matched cities were then randomly assigned within each state to one of three conditions: televised prevention training plus technical assistance, televised prevention training only, or prevention as usual (control). All community leaders within the same community were treated as one cluster. Thus, the research design constitutes a randomized trial, with communities randomly assigned to the intervention group. The measurement design is longitudinal, with data for this study drawn collected on a panel from baseline (fall 2001) through 18-month follow-up (spring 2003).

Study Participants

Community leaders were identified and recruited through a process of snowball sampling (Jasuja et al., 2005), which included three criteria: (a) representing one or more prevention stakeholders (education, law enforcement, parent groups, youth services, media, local government, business, health or medical profession, special or minority interest group), (b) being—or having the potential to be—a positive role model for youth, and (c) willing to participate in a prevention coalition for 2 years. Research staff conducted snowball sampling through a series of phone interviews, and detailed related information was provided (Riggs et al., 2008).

This sampling process resulted in a list of 1,041 potential participants (39–179 per city). Among these respondents, one community leader in each city was identified and trained annually to serve as a site facilitator for STEP, which included organizing other leaders for training and meetings, facilitating data collection, and collecting archival data on the meeting process. From the list of potential participants, site facilitators identified 709 individuals from 24 cities who were considered to be active in terms of having attended at least one community or coalition meeting during the previous 12 months.

Measures

Measures included a community leader survey and a network survey data. The community leader survey included 122 items that measured leader attitudes and behaviors regarding community readiness for prevention program implementation, individual leader skills and attitudes, and coalition functioning. Consistent with the prior study (Valente et al., 2007), we used measures of coalition functioning, planning, and adopting prevention programs. The outcomes consisted of four scales of organizational functioning ($\alpha = 0.83$), data-based planning ($\alpha = 0.87$), benchmark achievement ($\alpha = 0.88$), and prevention activity progress ($\alpha = 0.90$). Detailed information about scale development and measurement model analysis have been published elsewhere (Jasuja et al., 2005; Valente et al., 2007). These four scores were analyzed separately and were aggregated to an overall prevention planning and adoption score as one outcome.³ We included the four subscales, which comprise the

³An overall prevention planning composite score was generated on the basis of 4 separate planning scores by a confirmatory factor analysis with the EQS program (Valente, Chou, & Pentz, 2007).

composite measure to see how the network characteristics differentially influence each dimension of the outcome.

The second survey was the network survey that had three open-ended nomination questions that asked members to list up to seven people for each domain (advice, friendship, and discussion) to whom they go for advice about prevention issues, with whom they were friends, and with whom they discuss prevention issues. These different communication networks represent the same leaders with different functions. For each community, we computed network-level measurements of density and centralization based on degree centrality. Density was calculated as the number of linkages in a network, expressed as a proportion of the maximum possible number of ties, the number of links divided by $N(N-1)$. As for centralization measures, we first computed the actor-level centrality measures that are based on indegree and outdegree. Then we computed overall centrality of the network (i.e., centralization) based on these five centrality measures by using the following formula (Freeman, 1979):

$$\text{Centralization} = \sum (C_{\max} - C) / (n^2 - 3n + 2)$$

where C , actor-level centrality measure, was computed based on indegree and outdegree separately. Centralization was computed by the ratio of the sum of differences between the individual centrality scores of the most central point ($C_{\max}$) and those of all other points (C), to the maximum possible sum of differences⁴ (Scott, 2000). Centralization measures the degree of concentration in the distribution of centralities among the actors. It ranges from 0 to 1, with higher values indicating a more centralized network (i.e., population is more heterogeneous with respect to each centrality score). We wrote programs in the MATA language and executed them under the STATA (StataCorp, 2005) environment, which computed the network measurements in a manner similar to the network software UCINET (Borgatti, Everett, & Freeman, 2002), but is more efficient for multiple networks.

Data

Data from both surveys were merged within and across the two waves. We created the panel data from only those who completed both Waves 1 and 2 ($n = 255$). Additionally, the data for all respondents who completed either Wave 1 or Wave 2 surveys ($n = 821$) was used to check the validity of results with cross-sectional analysis. If we obtain similar results from both the panel and the cross-sectional data, we consider them as robust findings.

The estimated values of intraclass correlation of the outcomes at both Wave 1 and Wave 2 ranged from .08 to .26 for the panel data, and from .07 to .21 for the cross-sectional data. Because these values were low, there was no additional adjustment used for intraclass correlation and the unit of analysis was the community.

⁴For an ideal directed star-structure (See Freeman (1979) for a more complete discussion).

Statistical Analysis

To examine the effect of change in network centralizations on program adoption for a given level of density, we conducted regression analyses and used the following model:

$$Y_2 = a + b_1 Y_1 + b_2 T_x + b_3 C_1 + b_4 C_2 + b_5 D_1 + b_6 D_2 + e$$

where Y_2 is of the five outcomes in Table 1 at Wave 2 and Y_1 is the same outcome at Wave 1; T_x represents a treatment community; C_1 and C_2 represent network-level centralization at Waves 1 and 2, respectively; D_1 and D_2 represent network-level density at Waves 1 and 2, respectively; e is an error term; b represents the standardized coefficient. We did not include an interaction term between density (D) and centralization (C) in the above model because the model becomes quite complicated given our sample size ($n = 20$), and our main goal is to see the amount of partial regression coefficient of centralization taking density into account.

RESULTS

Respondents completed both a community leader survey and a network survey. Of the 709 active leaders, 670 (94.5%) completed either the community leader or the network survey at baseline. Among those, 555 (83%) completed baseline community leader survey, 531 (79%) completed baseline network survey, and 419 (63%) completed both community leader and network surveys. At 18-month follow-up, data were collected from 406 (57.3%) leaders. Among those, 227 (56%) completed the follow-up community leader survey, 219 (54%) completed the follow-up network survey, and 189 (47%) completed both the follow-up community leader and network surveys. There were 255 leaders (36% of 709 active leaders at baseline) who completed surveys at both waves of either community leader or network survey. Among those, 227 (89%) completed community leader survey, 217 (85%) completed network survey, and 189 (74%) completed both community leader and network surveys. Thus, there were 821 respondents at baseline and follow-up, and 255 respondents provided data at both waves. Missing data mainly came from refusal. Twenty of the 24 communities had complete data for both surveys at both waves. There were no coalition demographic or experimental group differences between the communities with complete versus incomplete data. The rate of attrition was not constant across communities. We conducted attrition analysis by computing pairwise correlation coefficient between the degree of dropout and any network or baseline outcome characteristics, and results showed no association at the alpha level of .05. Details of the intervention and community characteristics have been described previously (Valente et al., 2007).

Table 1 shows descriptive statistics of network indicators for three relations ($n = 20$ for both advice and discussion relations), and averages of the mean outcome scores of each community for Wave 1 and Wave 2 based on panel data ($n = 255$).⁵

As for the network indicators, size decreased significantly (partly due to the dropping of cases at Wave 2), but density also increased between the baseline and the follow-up for both

⁵For the descriptive statistics at the individual level cross-sectional data ($n = 821$), refer to the previous study at Table 1 (p. 882) (Valente, Chou, & Pentz, 2007).

relations. Centralization measures did not show any significant changes between the baseline and the follow-up for both relations. With regard to the adoption outcomes, none increased significantly. Here, we used the one-tailed *t*-test for the outcome changes because we expected the changes to increase.

Next, we conducted regression analyses using the panel data ($n = 255$) to examine the effect of change for both centralizations (indegree and outdegree) on adoption outcomes controlling for the density level of both the advice and the discussion networks. More specifically, we regressed the Wave 2 outcomes (Y_2) on their baseline score (Y_1), baseline density (D_1), baseline centralization (C_1), and Wave 2 density (D_2), and Wave 2 centralization (C_2). Table 2 shows the results of standardized regression coefficients.

For the advice network, we found a significant negative effect of the Wave 2 outdegree centralization on all outcomes ($b_4 = -.64$; $p < .01$ for functioning, $b_4 = -.46$; $p < .05$ for achievement, $b_4 = -.61$; $p < .05$ for progress, and $b_4 = -.47$; $p < .05$ for the combined scores) except data-based planning for a given level of density. Because baseline centralization was included in the model, the results indicate that centralization change was negatively associated with outcome change (Valente et al., 2007), meaning outcome scores were higher for coalitions that decreased their centralization (or lowered performance for those with increased centralization). For the discussion network, we found a significant positive effect of change in indegree centralization (C_2) on all outcomes ($b_4 = .70$; $p < .05$ for functioning, $b_4 = .61$; $p < .05$ for planning, $b_4 = .74$; $p < .05$ for progress, and $b_4 = .67$; $p < .05$ the combined score) except benchmark achievement. These results indicate that organizational functioning, data-based planning, or prevention activity progress were higher for coalitions that increased their centralization (or conversely resulted in lower performance for those with decreased centralization).

As for the effect of Wave 2 density (D_2), we found a significant negative association between change in density and all of the outcomes except achievement for both advice and discussion networks (advice network: $b_6 = -.90$; $p < .001$ for functioning, $b_6 = -.59$; $p < .05$ for planning, $b_6 = -.85$; $p < .001$ for progress, and $b_6 = -.76$; $p < .01$ for composite score; discussion network: $b_6 = -.73$; $p < .01$ for functioning, $b_6 = -.68$; $p < .01$ for planning, $b_6 = -.84$; $p < .01$ for progress, and $b_6 = -.72$; $p < .01$ for composite score), indicating that the coalition networks that decreased their density level had better adoption. These results are consistent with prior findings (Valente et al., 2007), showing that the significant decreased density on outcomes holds after controlling for the possible complementary effect of centralization.

For both advice and discussion networks, baseline outcome scores (Y_1) were also correlated with all follow-up outcomes (advice network: $b_1 = .54$; $p < .01$ for functioning, $b_1 = .55$; $p < .05$ for planning, $b_1 = .65$; $p < .001$ for achievement, $b_1 = .58$; $p < .01$ for progress, $b_1 = .66$; $p < .001$ for composite score; discussion network: $b_1 = .44$; $p < .05$ for functioning, $b_1 = .58$; $p < .05$ for achievement, $b_1 = .36$; $p < .05$ for progress, $b_1 = .43$; $p < .05$ for composite score), suggesting that the community-level perceptions were consistent over time, despite a substantial portion of different individuals in the community (Valente et al., 2007). Because the baseline score has a strong association to outcomes, we tested whether there were

significant changes in variance explained (R^2) by each variable in the model of composite outcome for both the advice and discussion networks. For the advice network, we found that 11% ($p < .05$) of additional variance was accounted for by adding changes in density, and another 12% ($p < .05$) of the variance was accounted for by adding changes in outdegree centralization to the model. For the discussion network, 10% variance was accounted for by adding changes in density (but it was not significant at the $\alpha = .05$ level), and another 15% ($p < .05$) of the variance was accounted for by adding change in indegree centralization to the model. Additionally, as a check for multicollinearity among our independent variables, we computed tolerance values (inverse of variance inflation factor) for both models of advice and discussion networks. We found that all variables have a tolerance value higher than .01, which implies that no independent variables were a linear combination of the others.

As for the results of baseline centralizations (C_1), only for the discussion network, they were significantly correlated with outcome change ($b_3 = -.42$; $p < .05$ for functioning, $b_3 = -.52$; $p < .05$ for progress, and $b_3 = -.34$; $p < .05$ for composite score), but none of the advice networks were. This suggests that some basic level of interpersonal communication and connections may have already existed beforehand for coalitions to generate better outcomes (Valente et al., 2007) when leaders discuss prevention issues; for the advice network, such basic network properties do not seem to matter in obtaining a better outcome. This makes sense, given that the discussion relation tends to be the one that is regularly reinforced, whereas the advice relation would be employed less frequently. Thus, the initial state of the discussion network has a much more dominant influence on the outcome.

With regard to the results of the intervention effect (T_x), there was no statistically significant association of the intervention and adoption for all outcome changes for the advice network for a given level of network indices and baseline scores. It must be noted that even though there was no direct effect of intervention on adoption, it might be possible that certain network properties may have an intervening effect on such relationships. On the other hand, we found that the discussion network had a significant positive effect on planning ($b_2 = .31$; $p < .05$), achievement ($b_2 = .37$; $p < .05$), and composite score ($b_2 = .26$; $p < .05$), which indicates that for a given level of network indices and baseline scores, intervention had a direct impact on adoption.

As a side analysis, we included the age of coalition (measured by the year with $M = 6$, $SD = 6.72$, $\min = 0$, $\max = 25$) as a control variable in our regression models considering the different types and phases of development of the participation coalitions.⁶ We found that the age of the coalition had a significant positive association with both functioning ($b = .25$; $p < .05$) and composite score ($b = .26$; $p < .05$) only for the advice network; however, it did not alter the significant effect of the centralization change (C_2) in outcomes.

Table 3 summarizes the standardized effect size of the change in centralization (Wave 2 centralization) on five outcomes for both panel and cross-sectional data ($n = 821$), which highlights our findings of the effects of network changes on each outcome.

⁶We appreciate an anonymous reviewer to point this out.

The results of outdegree centralization for the advice network were similar between panel and cross-sectional data. Cross-sectional data showed significant negative effects of change in outdegree centralization on functioning ($b_4 = -.41$; $p < .05$), achievement ($b_4 = -.45$; $p < .05$), progress ($b_4 = -.46$; $p < .05$), and the combined scores ($b_4 = -.36$; $p < .05$). The consistency of results for the advice data suggests some robustness to the results from the panel data.

With regard to the discussion network, results from the cross-sectional data showed a significant positive effect in change in indegree centralization only on progress ($b_4 = .58$; $p < .05$) and combined ($b_4 = .56$; $p < .05$) scores. In the cross-sectional data, the centralization effect on functioning and planning did not achieve statistical significance (detected in the panel data). This indicates that the robustness of the results from the panel data applies only to the progress and the composite subscales.

DISCUSSION

We used network analysis methods to explore the dynamics of coalition systems and their influence on the implementation of drug abuse prevention programs. Throughout this article, we stressed that network centralization is distinct from network density. Given this, our study addressed the question of how coalition centralization affects coalition networks' ability to adopt intervention programs for a given level of density. In so doing, we examined network degree-based centralizations and their associations with the adoption of prevention programs. From a system perspective, we also addressed the question of whether the different network relations produce distinct dynamics of coalition networks generated by centralization. We found that effective coalition networks for the diffusion of intervention programs can be achieved by (a) advice networks decreasing the concentration of influential leaders, and (b) discussion networks increasing the concentration of prominent leaders. These results imply that optimal collaborative coalition networks might be realized by limiting the density in such a manner that distributes the power/influence among a broader base of coalition members via advice, while condensing the decision-making body to just a few prominent leaders (so as to efficiently decide how they will implement adoption through discussion), i.e., increasing the number of prominent leaders who discuss prevention while reducing the number of leaders people need to seek advice from to take action.

These conclusions are restricted by some of the limitations in our study. First, we had a limited number of communities to examine the complicated relations between network indices and intervention outcomes. We assumed the effect of centralization on outcomes is constant across density level, but it may be that this is not the case. Future research should investigate this issue with larger sample size. Second, for the discussion network, we could not obtain validation of the results between the panel and the cross-sectional data with regards to their statistical significance on adoption outcomes. Therefore, results should be interpreted with caution. Third, we used self-reported attitudes and practices that may have deviated from actual program adoption. Lastly, the current study examined the effect of centralization based on degree centrality, but other centralizations measurements (based on closeness or betweenness centrality) that take indirect links into account may have a different effect on outcomes.

Despite these limitations, our study offered an empirical investigation of the dynamic nature of coalition networks in relation to its influence on the coalition's ability to employ evidence-based drug abuse prevention program by describing the changes in network centralization. Our study suggests the necessary network-level properties used to understand how to optimize community network structures for the adoption of public health programs. Future studies will benefit by considering the attitudes and behaviors of central leaders in these networks.

IMPLICATIONS FOR PRACTICE

A major trend in public health research is translational research, part of which refers to the translation of research findings to real-world practice (Pentz, 2008). Although it makes intuitive sense to assume that a coalition would cast its net broadly outward to get advice on how to promote prevention in its community, and then bring back the accumulated information to discuss and decide upon among the more central coalition leadership, these patterns have not been systematically evaluated in research. For real-world practice, this finding suggests that coalitions should actively seek technical assistance for promoting evidence-based prevention that goes beyond their initial or central leadership. The information should then be discussed among a smaller leadership group before being considered for adoption by the whole coalition. The findings also suggest that as soon as possible, coalitions should distribute workloads or tasks among its members to increase progress in adopting evidence-based prevention. The timeframe evaluated in this study suggests that all of these changes can be achieved within 18 months or less, and result in significant progress towards adopting evidence-based prevention programs.

The results of this study have additional implications for practice. Too often it seems, the actual tasks of prevention are repeatedly assigned to the same few individuals within a coalition, based on the mistaken assumption that that type of work assignment will be more efficient or yield a better work product. The findings of this study argue otherwise, and are consistent with results of other studies which suggest that workloads distributed over too highly centralized and dense networks may result in greater burn-out over time (Butterfoss et al., 1996; Zakocs & Edwards, 2006). Some interventions that are designed to build community coalition capacity, such as the STEP intervention reported here, encourage coalitions to provide for planned turnover with the replacement of some members to help prevent burn-out (Riggs et al., 2008; Riggs & Pentz, 2007). Viewed in this manner, coalition member turnover can and perhaps should be treated as a positive rather than negative indicator of coalition functioning. Finally, results imply that practitioners might want to consider developing coalitions that are smaller and flexible in their functioning, i.e., large size is not an indicator of community coalition effectiveness in promoting evidence-based prevention.

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Table 1
Descriptive Statistics of Coalition Network Indicators and Outcomes for T1 and T2 at the Community Level

<i>Network indicators</i>	<i>Wave 1 M</i>	<i>Wave 1 SD</i>	<i>Wave 1 Range</i>	<i>Wave 2 M</i>	<i>Wave 2 SD</i>	<i>Wave 2 Range</i>	<i>Unpaired t</i>	<i>p</i>
Size								
Advice	24	7.22	13–41	14	8.37	4–33	–4.15	0.00 ^a
Discussion	24	7.22	13–41	14	8.37	4–33	–4.15	0.00 ^a
Density								
Advice	.11	.04	.04–.18	.15	.06	.05–.33	2.37	0.02 ^a
Discussion	.12	.05	.06–.21	.15	.04	.06–.21	1.90	0.07 ^a
Indegree central								
Advice	.35	.12	.17–.55	.39	.11	.15–.55	1.25	0.22 ^a
Discussion	.36	.13	.13–.56	.40	.19	.15–.87	0.81	0.42 ^a
Outdegree central								
Advice	.16	.04	.08–.23	.15	.07	.00–.24	–0.12	0.91 ^a
Discussion	.14	.04	.08–.21	.17	.10	.03–.42	1.51	0.14 ^a
Adoption outcomes								
Functioning	3.71	.35	2.89–4.30	3.69	.34	3.07–4.45	–0.21	0.58 ^b
Planning	3.01	.24	2.53–3.49	3.02	.21	2.53–3.47	0.14	0.44 ^b
Achievement	2.07	.28	1.42–2.61	2.18	.22	1.82–2.66	1.37	0.09 ^b
Progress	2.12	.29	1.56–2.58	2.12	.18	1.73–2.42	–0.06	0.52 ^b
All four standardized and combined	.00	.85	–2.0–1.67	–.06	.84	–1.58–1.41	–0.22	0.59 ^b

Note. *N* = 20 with complete, merged network and community leader data.

^aTwo-tailed *t* test.

^bOne-tailed *t* test.

Table 2

Effects Standardized Coefficients of Baseline Scores, Baseline Centralization, Follow-Up Centralization, Baseline Density, and Follow-Up Density on Community-Level Attitudes and Practices Regarding Adoption of Evidence-Based Substance Abuse Prevention Programs

	Functioning <i>b</i>	Planning <i>b</i>	Achievement <i>b</i>	Progress <i>b</i>	Composite scores <i>b</i>
Advice					
Baseline score	.54**	.55*	.65***	.58**	.66***
Intervention	-.14	.23	.25	-.29	.04
Wave 1 density	.31	.50*	.23	.47*	.44*
Wave 1 outdegree centralization	-.27	-.21	-.22	-.14	-.26
Wave 2 density	-.90***	-.59*	-.34	-.85**	-.76**
Wave 2 outdegree centralization	-.64**	-.03	-.46*	-.61*	-.47*
Adjusted R ²	0.63	0.46	0.64	0.51	0.69
Discussion					
Baseline score	.44*	.22	.58*	.36*	.43*
Intervention	.16	.31*	.37*	-.001	.26*
Wave 1 density	.35	.53*	.32	.62*	.49*
Wave 1 indegree centralization	-.42*	.04	-.36	-.52*	-.34*
Wave 2 density	-.73**	-.68**	-.36	-.84**	-.72**
Wave 2 indegree centralization	.70*	.61*	.41	.74*	.67*
Adjusted R ²	0.47	0.72	0.52	0.55	0.66

Note. *N*=20 with complete, merged network and community leader data.

* $p < .05$;

** $p < .01$;

*** $p < .001$.

Table 3

Summary of the Standardized Effect Size of Change in Wave 2 Centralization on Adoption Outcomes, Adjusting for All Variables in the Model, By Data Type and Network Type

	<i>Advice network outdegree centralization</i>	<i>Discussion network indegree centralization</i>
Functioning		
Panel	-.64 ^{**}	.70 [*]
Cross-sectional	-.41 [*]	.39
Planning		
Panel	-.03	.61 [*]
Cross-sectional	.10	.42
Achievement		
Panel	-.46 [*]	.41
Cross-sectional	-.45 [*]	.52
Progress		
Panel	-.61 [*]	.74 [*]
Cross-sectional	-.46 [*]	.58 [*]
Composite scores		
Panel	-.47 [*]	.67 [*]
Cross-sectional	-.36 [*]	.56 [*]

Note. $N=20$ with complete, merged network and community leader data.

^{*}
 $p < .05$;

^{**}
 $p < .01$;

^{***}
 $p < .001$.