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Not getting high with a little help from your friends: Social versus drug network correlates of marijuana use among YMSM

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Abstract

Substantial evidence has documented the importance of social connections in shaping health and drug use behaviors among adolescents and young adults. The current study extends previous research into the associations between network characteristics and drug use behavior among young men who have sex with men (YMSM) by 1) examining multiple network characteristics, 2) simultaneously assessing multiple network types (i.e., social and drug use), and 3) examining change in network characteristics and drug use behavior over time. Data for the current study comes from RADAR, a longitudinal cohort study of YMSM. Latent growth curve models examined the change in frequency of marijuana use across four observations and individual and network correlates of this change including: demographics, drug network size, drug network density, social network size, and social network density. Baseline frequency of marijuana use was positively associated with drug network size and density, while it was inversely related to social network size and density. In addition, increasing frequency of marijuana use was associated with increases in drug network size and density, while it was associated with decreases in social network size. These findings highlight the complexity of multiple network types (e.g., drug and social) and network structures (e.g., size and density) in understanding drug use behavior among YMSM. Furthermore, as changes in drug and social networks may be indicative of changes in marijuana use, peer relationships may be especially important in understanding an individual's trajectories of marijuana use.

Introduction

Social networks, or the structure of relationships among individuals, have been frequently used to understand drug use behavior, particularly among adolescents and young adults. For example, peers in adolescent networks provide an important source of social influence on drug use behavior [1–4], are linked to drug use initiation [5, 6], and are a common source for obtaining drugs [7, 8]. Despite the importance of social networks in understanding drug use behavior in adolescents and young adults, the analysis of social network correlates of drug use has suffered from three common limitations; these studies: 1) have mainly focused on the composition of these networks (e.g., what percentage of friends use drugs) rather than structural properties (e.g., connections among network members, 2) have emphasized social

ties such as “friendship” networks [9–11] rather than other forms of network ties (e.g., drug use), and 3) are dominated by cross-sectional research rather than longitudinal studies.

First, while the impact of social network composition certainly merits investigation, compositional effects alone are unlikely to fully capture the complexity of how social networks influence drug use behaviors. For example, denser peer social networks predicted higher likelihood of drug use over time [12] and a stronger connection between an adolescent’s delinquent behavior (e.g., “drank alcohol” or “got drunk”) and one’s peer’s behavior [10, 13], potentially due to greater ease of norm enforcement in more tightly-knit social networks [14–16]. Although studies like these are increasingly common, a greater understanding of structural network characteristics and their association with drug use behavior could provide valuable insight into dynamics of drug use behavior among young adults.

Second, most studies only examine a single type of network connection, most frequently the social network such as friendship networks [17]. However, other network types such as drug use networks (i.e., individuals one uses drugs with) have received less attention, but may provide important information that is not typically captured in social networks alone. For example, Barman-Adhikari et al. [18] found strong associations between an individual’s proximity to peer drug use and their own drug use behavior in a study of homeless youth. Similarly, a preliminary study found that an individual’s drug use network density was associated with higher levels of drug and alcohol use [19]. Furthermore, one of the most common drug use behaviors in youth – marijuana use – has received less attention versus network correlates of injection drug risk behavior [20] or sexual risk behavior [16, 21]. Accordingly, this study attempts to simultaneously examine and compare multiple network types (i.e., drug and social networks) to better understand their association with the most common drug use behavior (i.e., marijuana use).

Third, longitudinal studies of social networks and drug use behavior remain relatively rare, but are essential for understanding social influence processes and diffusion of behavior [22]. Those studies that have examined longitudinal change have largely relied on bounded networks within predefined populations of schools [23–26]. While these studies have substantial advantages, they also are limited by only including ties within this bounded population and therefore may leave out important sources of influences (e.g., adults or friends outside of school). In contrast, personal network (i.e., ‘egocentric network’) studies are able to more thoroughly examine the perceived networks surrounding participants and potential sources of influence, but they have less commonly included longitudinal components. Furthermore, the small number of personal network studies [27, 28] that have examined the relationship between drug use behavior and change in network characteristics have focused on size or turnover (i.e., the number of constant members versus members that left or entered the network), but not the change structural characteristics – like density - which may provide additional insight into the social context of drug use.

Accordingly, the current study expands upon previous work by longitudinally examining the structural characteristics of both drug and social networks in an effort to provide a more comprehensive picture of the association between change in network characteristics and

drug use behaviors over time. Data for this study come from an ongoing longitudinal cohort study of young men who have sex with men (YMSM). YMSM experience drug use rates higher than their heterosexual peers [29, 30] yet most network research with YMSM has focused on social or sexual networks rather than drug use networks. Accordingly, this sample represents an important subpopulation for drug use epidemiology generally, and one in which little is known about the associations between drug and social network structures and drug use behaviors.

Method

Participants

Individuals were enrolled into RADAR, a longitudinal cohort study of YMSM to investigate multilevel drivers (individual-, dyadic-, network-, and biologic-level characteristics) of HIV infection and substance use. Potential participants could be recruited for the cohort in one of three ways: (1) involvement in a prior cohort of YMSM and/or lesbian, gay, bisexual, or transgender (LGBT) youth; (2) through being a serious partner of a RADAR cohort member; or (3) through peer recruitment by a RADAR cohort member. Recruitment for the two prior cohort studies [31, 32] was through a mix of modified respondent-driven sampling, venue-based recruitment, and online recruitment. Serious partners were defined as someone the participant was “in a serious relationship with” the decision of who met this criterion was left to the participants themselves to determine. However, all cohort members were between 16 and 29 years of age, born male, English speaking, and either reported a sexual encounter with a man in the previous year or identified as gay or bisexual. Interviews are still ongoing, but a total of 708 out of 858 eligible cohort members had completed their fourth interview (i.e., roughly 2 years since baseline interview) by the time of data analysis (i.e., 82.5% completion rate) and were therefore examined for inclusion in longitudinal analysis. Of these individuals, 589 (83.1%) used marijuana at least once during the 30 days prior to at least one study visit, and were included in the analysis.

Procedure

Participants completed interviews for this study every six months. At each visit, participants completed a network interview, self-reported psychosocial survey, and biomedical specimen collection (HIV, STI, and/or drug screening). Participants were compensated \$50 for each visit, and all study activities were approved by the Northwestern University Institutional Review Board. Data collection began in February 2015; this manuscript utilizes data collected through February 2018.

Measure

Network Inventory—Data for this study come from an interviewer-assisted touchscreen network interview protocol (netCanvas-R) used to elicit data about the social, drug, and sexual connections (i.e., alters) of participants. Comprehensive details on this network interview can be found elsewhere [33]. In brief, the tool is structured so that social, drug, and sexual alters are first named by the study participant, and then the relationship role(s) of the alters are identified. Next, important attributes of these alters are captured, along with attributes of the connections between the participant and alters. Finally, several interactive

maps of the network members are generated in which participants can code relations between alters (i.e., if the participant perceives two of their network members interact regularly, use drugs together, or have had sex).

Alters were elicited using five name generators: individuals the participant is “closest to” (i.e., “the people you are closest to, that is, people you see or talk to regularly and share your personal thoughts and feelings with”), individuals the participant used marijuana or other drugs with during the last six months, individuals the participant had sex with during the last six months, individuals the participant perceived to have used drugs with two or more of their alters, and individuals the participant perceived to have had sex with two or more of their alters. As noted, after the name generation process, information was gathered on alter attributes (e.g., age, gender identity, race/ethnicity), tie types with these alters, and perceived ties between alters. For each type of alter-to-alter tie used in this study (i.e., drug or social), the participant was presented a separate interface showing all network members, regardless of how they were elicited, and asked to indicate which of the alters were connected for the given tie (e.g., ‘used drugs together’). For the current analysis, *Drug use network size* indicated the number of alters with whom the participant indicated using any drugs with during the prior six months (i.e., number of drug use partners). Although our main outcome focuses on marijuana use, alters were included in this network if the participant reported drug use of any kind with those alters. *Social network size* indicated the total number of alters the participant named during “closest” name generator or indicated they were “very close” to in a question regarding the closeness to each network member (i.e., “Do you consider your relationship to be very close, somewhat close, or not close at all?”). Accordingly, alters were considered social connections if the participant indicated that they were very close to that individual, regardless of other roles (e.g., family, mentor, sex partner, drug partner) that individual may have been nominated for. Importantly, the measures of network size were not mutually exclusive so alters could appear in both the drug and social network if they met the given criteria for that network, as described above. However, because both variables were included in the same model, we were able to evaluate the independent contribution of network size for each network type. *Drug use network density* represented the average number of drug ties between alters who used drugs with the participant (i.e., ties to the participant were not included). This measure has been used in previous studies of drug and sexual networks [19, 34] and was chosen as the measure of connectivity, in contrast to the traditional measure of egocentric network density, because it is less strongly correlated with network size and therefore limits collinearity between the measures of network size and density. *Social network density* represented the average number of social ties between alters who were close social ties to the participant (i.e., ties to the participant were not included). Finally, change in size and density for both drug use and social network are simply the difference between these metrics at the fourth visit and those at the first (e.g., change in drug size = drug network size wave 1 – drug network size wave 4).

Drug Use—The primary outcome of our analysis is frequency of marijuana use in the past 30 days. This focus was primarily because marijuana was by far the most commonly used drug among participants with 69.1% of sample participants reporting marijuana use in the

past six months at baseline, well above the second most common drug (i.e., inhalants) reported by only 14.5% of participants. To measure frequency of marijuana use, participants were asked: “On how many occasions have you used marijuana (also called ‘Weed’ or ‘Pot’) in the past 30 days?” and asked to respond on an ordinal scale (1 = Not in the past 30 days to 7 = 40 or more times).

Statistical Analysis

A latent growth model approach [35] was used to model the association between individual demographics, baseline network characteristics, change in network characteristics, and marijuana use frequency over time. Latent growth models enable the estimation of baseline level (intercept) and change in the outcome across observations (slope) as well as the inclusion of correlates of both the intercept and the slope. The mean estimate for the intercept and slope parameters represents the average estimated value of those parameters across individuals, while the variance parameter represents how individuals vary in their estimates (i.e., did people start at different frequencies of use or change at different rates). We conducted an iterative approach to model selection. The first model (Model 1) was an intercept only model allowing individuals to vary in their frequency of marijuana use but modeling no change in use across observations. Model 2 added a random slope term enabling variation in linear change in frequency to vary across observations. Finally, Model 3 added all correlates of the intercept and slope, enabling the examination of correlates of initial frequency and change in frequency of marijuana use. Correlates of the intercept included: age at baseline, race/ethnicity, drug use network size, drug use network density, social network size, and social network density. Correlates of the slope included the same variables in addition to four additional terms indicating the change in baseline to the fourth visit for each network characteristic.

All models were evaluated using the following absolute fit indices: approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). However, because Model 2 was nested within Model 1, Model 2 were evaluated relative to Model 1 using the change in χ^2 , as this test determines if freeing the slope parameter significantly improves model fit. However, Model 3 was not nested within Model 2 because it includes additional independent variables and therefore was only evaluated using absolute fit indices. All analyses were performed in Mplus 7.3 [36]. Maximum likelihood with robust standard errors (MLR) was used as the estimator. As a full information approach, this approach utilizes all possible data to inform each parameter and therefore improves upon simpler forms of handling missing data such as listwise deletion [37]. In addition, MLR is also appropriate and provides accurate standard errors for ordinal variables with at least 6 categories, even in the presence asymmetry in the frequency of those categories [38].

Results

Descriptive statistics of the 589 marijuana using participants included in the analysis can be found in Table 1. Cohort members were mostly Black (37%) and Latino (32%) with a mean age of 21.37 years (SD = 2.92). At baseline, participants reported an average of 11.03 (SD = 6.28) close social ties and 5.83 (SD = 5.89) drug use partners. The correlation matrix for

network characteristics can be found in Table 2 describing the association between network characteristics. These characteristics were moderately correlated with each other, with the magnitude of correlations ranging from 0.03 to 0.64.

Latent Growth Models

The intercept, slope, and model fit statistics for each model are presented in Table 3. Model 1 showed significant misfit ($\chi^2 = 67.07$, $p < 0.001$) and poor fit for RMSEA (0.11) but good fit on other indices (CFI = 0.95, TLI = 0.96). Although the model had significant misfit with the chi-square test, this test is likely to detect trivial misfit with large sample sizes and therefore should be interpreted in the context of the other fit indices that are a function of the chi-square statistic [39]. Model 2 sufficiently improved the fit of the model ($\chi^2 = 54.04$, $p < 0.001$) and, although the model still had significant misfit ($\chi^2 = 13.02$, $p = 0.023$), showed excellent fit on all other indices (RMSEA = 0.05, CFI = 0.99, TLI = 0.99). Furthermore, both the intercept and the slope of Model 2 had significant variation indicating individuals varied in both their initial level and change in marijuana use frequency which could potentially be explained by individual or network characteristics. Accordingly, Model 3 was examined where all covariates of the intercept and slope were added to the model. The model again had significant misfit ($\chi^2 = 73.09$, $p < 0.001$) but indicated good (CFI = 0.96, TLI = 0.96) or excellent (RMSEA = 0.05) fit on all other indices.

The parameters for Model 3 indicated there remained a significant increase in frequency of marijuana use across observations ($\mu = 0.44$, $SE = 0.20$, $p = 0.031$). Furthermore, Table 4 presents the associations between all correlates of both the intercept and the slope. The baseline drug network size ($b = 0.183$, $SE = 0.015$, $p < 0.001$), drug network density ($b = 0.336$, $SE = 0.082$, $p < 0.001$), social network size ($b = -0.053$, $SE = 0.014$, $p < 0.001$), social network density ($b = -0.123$, $SE = 0.059$, $p = 0.039$), and age ($b = 0.136$, $SE = 0.025$, $p < 0.001$) were all significant predictors of the baseline frequency of marijuana use. Similarly, baseline drug network size ($b = 0.024$, $SE = 0.007$, $p = 0.001$), change in drug network size ($b = 0.070$, $SE = 0.006$, $p < 0.001$), change in drug network density ($b = 0.06$, $SE = 0.026$, $p = 0.019$), and change in the number of social network members ($b = -0.011$, $SE = 0.004$, $p = 0.013$) were significant correlates of change in frequency of marijuana use (i.e., slope). Change in the density of social network members was not a significant correlate of change in frequency of marijuana use.

Discussion

This study expands upon previous work by longitudinally examining the structural characteristics of both drug and social networks in an effort to provide a more comprehensive picture of networks correlates of drug use behaviors over time. We found that individuals with larger and more dense drug use networks had more frequent marijuana use. However, we also found that larger and more dense social networks were associated with less frequent marijuana use. The inverse association between social network size and density and frequency of drug use suggests that social networks – unlike drug networks – may provide a protective effect. Previous studies have indicated the density of social networks are closely associated with risk behavior norms in both sexual [40, 41] and drug risk behavior

[15]. Furthermore, one study found that denser social networks were associated with a lower likelihood of substance use among women one year after treatment [42], while another [43] found social network density inversely associated with problem drinking. Similarly, the protective effect found in the current study may potentially be explained by increases in social support – or perhaps the increase in norm enforcement and social monitoring provided in dense networks.

Contrastingly, a number of studies suggest tightly knit social networks may cultivate a culture of substance use among adolescents and young adults [44, 45], such as a culture of drinking [46, 47]. Relatedly, other studies have found that dense social networks are associated with drug risk behavior [48] and lower levels of HIV prevention norms [16]. However, given that most of these previous studies focused on a single network type, they may have been unable to disentangle the network effect of high-risk (e.g., drug use) versus low-risk (e.g., social support) networks. For example, one study [49] found that drug network size was positively associated with frequency of injection drug use but social network size had no significant correlation. Similarly, by separately measuring these two network types, the current study was able to document the differential associations of each network type.

Finally, this study found that changes in social and drug networks were associated with marijuana use frequency. Both social and drug network size were associated with change in marijuana use frequency, indicating that individuals with growing drug use networks and shrinking social networks were more likely to increase their frequency of use. This finding suggests that increasing frequency of use is related to peer relational processes. Although it is outside the scope of this study to identify these specific processes – future work should examine the relationship between the frequency of marijuana use and increases in social isolation, or perhaps decreases in social support that are relevant to the reduction in drug use. Indeed, previous research suggests that non-drug using network members might be useful sources of support for reduction in drug use [50–52]. Notably, changes in drug network density and baseline drug network size were associated with changes in marijuana use frequency. However, changes in social network density and baseline social network size had no significant associations with changes in marijuana use frequency. This may suggest that the size and structure of the drug network may be more closely associated with drug use trajectories, as compared to close social connections.

These findings also support the relevance of peer relationships in shaping adolescent drug use specifically among YMSM. As sexual and gender minority youth often experience rejection and social isolation [53] – substance use interventions within this population should focus their strategies not only on the individual, but also on understanding and improving the social support systems around the individual. By ensuring that minority youth have access to supportive peers who are able to enforce healthy norms for substance use, minority youth may be better protected.

A primary limitation of the current study is that all data on social network characteristics was derived from self-report by participants. Accordingly, it is unclear if their perceptions of their network members, particularly perceived ties between alters, are accurate. For example,

the validity of perceived drug network ties between alters is unclear and this perception may itself be biased by perceived norms regarding drug use by one's peers. Nonetheless, previous work has shown that there is substantial overlap in perceived peer drug use and actual peer drug use [54], although participant accuracy of reporting data on alters remains an area of significant debate [55]. Secondly, for the longitudinal analysis, the small number (i.e., four observations) of measurement occasions limits our ability to make inferences regarding the time order of events or examine more complex trajectories of drug use (e.g., unique classes of trajectories). For example, we focused on a simple linear model of change over a relatively short period of two years. Yet, longer-term longitudinal studies suggest that there is substantial variability in young adult and adolescent drug use trajectories [56], and external influences may also vary in their impact over different developmental periods [57] including peer drug use [58]. Furthermore, while the current sample reflects an important subpopulation for the epidemiology of drug use, the sample was not drawn using probability sampling and therefore the findings cannot be generalized to a larger population. Finally, while this analysis explored how different network structures and types impact drug use behavior. It is equally important to contrast the impact of network composition versus network structure [1]. Future studies should continue to explore the numerous ways social and other network characteristics are associated and influence drug use behavior.

Despite these limitations, this study offers a rare picture of the structural properties of multiple network types among young adults and how change in these properties are associated with drug use behavior over time. The findings document both the risk associated with dense and large drug use networks, as well as the protective association of larger and dense social networks. Given that these findings suggest that drug and social networks are indicative of changes in marijuana use, peer relationships may be especially important in understanding and in intervening on an individual's use of marijuana.

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Table 1.

Descriptive Statistics (n = 589)

	n (%)	M (SD)
Marijuana Frequency (last 30 Days) *		
0 Times	683 (29.0)	
1 – 2 times	362 (15.4)	
3 – 5 times	269 (11.4)	
6 – 9 times	156 (6.6)	
10 – 19 times	248 (10.5)	
20 – 39 times	275 (11.7)	
40 or more times	363 (15.4)	
Drug Network		
Size		5.83 (5.89)
Density		1.10 (1.08)
Change in Size		–0.54 (5.42)
Change in Density		0.01 (1.27)
Social Network		
Size		11.03 (6.28)
Density		2.21 (1.48)
Change in Size		2.39 (6.19)
Change in Density		–0.17 (1.52)
Age (At Baseline, Years)		21.37 (2.92)
Race/Ethnicity		
Black/African-American	217 (0.37)	
Latino/Hispanic	190 (0.32)	
Other	58 (0.10)	
White	124 (0.21)	

* Frequency of drug use for all observations.

Table 2.

Correlation Matrix of Network Characteristics

		1	2	3	4	5	6	7	8
Drug Network	1. Size	-							
	2. Density	0.451	-						
	3. Size	-0.639	-0.230	-					
	4. Density	-0.164	-0.581	0.363	-				
Social Network	5. Size	0.347	0.176	-0.148	-0.079	-			
	6. Density	0.276	0.399	-0.204	-0.274	0.431	-		
	7. Size	-0.097	-0.026	0.282	0.193	-0.298	-0.114	-	
	8. Density	-0.132	-0.248	0.261	0.388	-0.201	-0.630	0.255	-

Note. Bolded values are statistically significant associations with $p < 0.05$

Table 3.

Intercept and Slope Parameter Estimates with Model Fit Statistics

	Model 1	Model 2	Model 3
	Estimate [95% CI]	Estimate [95% CI]	Estimate [95% CI]
Intercept			
Mean	3.505 [3.349, 3.661]	3.91 [3.121, 3.461]	0.011 [-1.149, 1.171]
Variance	3.276 [2.849, 3.703]	3.382 [2.854, 3.911]	1.981 [1.603, 2.359]
Slope			
Mean	-	0.151 [0.098, 0.204]	0.444 [0.040, 0.848]
Variance	-	0.150 [0.080, 0.220]	0.093 [0.031, 0.156]
Intercept with Slope		-0.138 [-0.281, 0.005]	-0.103 [-0.224, 0.018]
Model Fit Statistics			
AIC/BIC	9327.34 / 9353.61	9279.30 / 9317.70	8354.46 / 8479.66
χ^2	67.07, p < 0.001	13.02, p = 0.023	73.09, p < 0.001
χ^2		54.04, p < 0.001	-
RMSEA [90% CI]	0.11 [0.08, 0.14]	0.05 [0.02, 0.09]	0.05 [0.03, 0.06]
CFI/TLI	0.95, 0.96	0.99, 0.99	0.96, 0.96

Note. χ^2 from Model 2 to 3 is not included because Model 3 is not nested within the previous model.

Table 4.

Correlates of Marijuana Frequency Intercept and Slope in Model 3

	Intercept Estimate [95% CI]	Slope Estimate [95% CI]
Age	0.136 [0.087, 0.086]	−0.015 [−0.032, 0.002]
Race		
Black (Reference)	-	-
White	−0.396 [−0.802, 0.010]	−0.020 [−0.163, .123]
Latino	−0.220 [−0.565, 0.125]	0.010 [−0.110, 0.129]
Other/Multiple	−0.068 [−0.590, 0.455]	−0.017 [−0.198, 0.163]
Network Characteristics		
Drug Network		
Size	0.183 [0.153, 0.212]	0.024 [0.010, 0.037]
Size	-	0.070 [0.058, 0.083]
Density	0.336 [0.176, 0.497]	−0.017 [−0.085, 0.052]
Density	-	0.060 [0.010, 0.110]
Social Network		
Size	−0.053 [−0.081, −0.026]	−0.008 [−0.019, 0.002]
Size	-	−0.011 [−0.019, −0.002]
Density	−0.123 [−0.239, −0.006]	0.028 [−0.021, 0.076]
Density	-	−0.022 [−0.062, 0.018]

Note. Estimates are presented with standard errors in parentheses. Bolded estimates represent statistically significant associations with $p < 0.05$