SciMedCentral

Journal of Substance Abuse & Alcoholism

Research Article

Population-Level Network Structure over Time and Marijuana Use among Homeless Youth

Eric Rice[1]*, Amanda Yoshioka-Maxwell[1], Harmony Rhoades[1], Hailey Winetrobe[1], Robin Petering[1], and Anamika Barman-Adhikari[2]

[1]*Department of Children, Youth and Families, University of Southern California,USA*
[2]*Graduate School of Social Work, University of Denver, USA*

***Corresponding author**

Eric Rice, Department of Children, Youth and Families, University of Southern California, Los Angeles CA 90089, USA, Tel: 213-821-4292; Email: ericr@usc.edu

Submitted: 21 December 2016

Accepted: 17 January 2017

Published: 19 January 2017

Copyright

© 2017 Rice et al.

OPEN ACCESS

Keywords

- Homeless youth
- Social networks
- Marijuana abuse

Abstract

Homeless youth report more marijuana use than stably housed youth; their marijuana use has been linked to the marijuana-using behaviors of their peers. This study was the first to examine the process of network influences in marijuana use with population-level (sociometric) social network data over time. Network data were collected from a population of homeless youth recruited from a drop-in center in Los Angeles every 6 months for 1 year (n = 237, 263, and 312). For each panel, a sociomatrix was generated based on youth nominating other youth in the sample. Degree centrality, betweenness, eigen vector centrality, and number of marijuana-using linkages represented network influence; logistic regression assessed associations with heavy marijuana use. Approximately 60% of the network membership changed between panels. Individuals with more network connections to other heavy marijuana users and youth with more connections to any other youth reported more heavy marijuana use. These results suggest that in transient, high-risk populations, social influence processes largely affect individual substance use patterns. Heavy marijuana use appears to be popular and important to the construction and reconstruction of these networks over time.

INTRODUCTION

As many as 2 million youth run away or experience homelessness in the United States each year [1-3], nearly 75% of whom report having used alcohol or marijuana, in addition to high rates of other illicit drug use [4-6]. Homeless youth use marijuana at much higher rates than housed youth; as much as 66% of homeless youth have reported daily marijuana use during the previous month and many meet criteria for marijuana abuse or dependence [7-9]. Recent studies have shown that marijuana use significantly affects adolescent cognitive function via negative effects on attention, spatial learning, and memory, beyond the effects of acute intoxication [10]. Furthermore, ongoing heavy marijuana use (daily use for at least 2 years) among adolescents younger than age 25 may have a negative cumulative effect on brain development over time, and younger age at onset of use may predispose these young people to brain damage [12].

Recent research has suggested that connections to other homeless peers are critical to the marijuana-using patterns of homeless youth [10,13]. Studies on substance use among homeless youth in general have consistently demonstrated that an individual's pattern of use is associated with peer use [5,14,15,16,17]. More importantly, homeless youth tend to engage in drug use at higher frequencies when their networks contain higher concentrations of drug-using peers [18], especially other homeless youth who use substances [13,15]. To date, research on how social network processes are associated with marijuana use has relied exclusively on what social network researchers call egocentric network data. These data are collected from individuals in the context of standard sampling techniques that involve survey respondents describing in detail their personal social network. To the best of our knowledge, no studies to date have examined marijuana use among homeless youth in the context of what network researchers call sociometric or whole-network data. Such data link a population of individuals of interest and reveal the ties among members of that population to determine how both direct and indirect linkages in a population are associated with behaviours of interest. Sociometric data describe the larger set of relationships, including linkages among many respondents [19,20]. This approach allows a better understanding of the patterns and influence of risk behaviour in the entire network and provides the opportunity to assess larger social structures that cannot be reduced to individual-level factors [20]. The present study sought to extend the examination of the impact of networks on marijuana use by investigating how sociometric network properties and positions in a larger interconnected network of homeless youth are associated with the marijuana use of individuals in that network.

The extant work examining risk taking among homeless youth using sociometric data is extremely limited. Rice and colleagues found that sexual risk taking [13], and use of methamphetamines

[21], were more likely to be reported by youth occupying the core positions in a network of homeless youth sampled in 2008. Additionally, previous work with these data has shown that among some groups of homeless youth, having more methamphetamine-using peers affects individual methamphetamine use. Given the high prevalence of marijuana use in this population and prior findings suggesting that substance use among homeless youth is associated with peer substance use, we hypothesized that compared to youth who are not heavy marijuana users, youth who report heavy marijuana use would also report more connections to other heavy marijuana users in the network.

These data, however, do not capture the dynamics of network engagement over time. Conceptually, Whitbeck [22] and others [9,13,23,24], have suggested that two distinct types of peer engagement exist among homeless youth (a) some youth become embedded in networks of other high-risk homeless youth and (b) other youth may never become fully embedded in such networks and thus maintain healthier behaviours. To fully explore this hypothesis, sociometric data over time must be examined. Perhaps the greatest challenge to date in conducting a longitudinal sociometric study with homeless youth is the simple fact that homeless youth constitute what social network researchers refer to as an unbounded population [25]. The population of homeless youth in any given city at any given point in time is an open system with relatively fluid membership. Who is on the street or living in a particular neighbourhood changes rapidly as new youth run away, others are incarcerated, and some find stable housing. The present study not only expanded understanding of how connections in networks affect the marijuana use of homeless youth, but did so by exploring these network dynamics over time.

METHODS

Sampling strategy

Because of the methodological and fieldwork complexities of collecting sociometric data on unbounded populations, this study was the first to collect sociometric data over time among homeless youth. We employed the event-based approach (EBA) proposed by Freeman and Webster [26] to create a boundary for this otherwise unbounded population. EBA creates a boundary from which to sample youth, does not depend on specific membership in a formal group, and allows social isolates and peripheral youth to be as equally represented as highly interconnected youth. EBA allowed us to impose constraints on the edges of this population by setting the boundaries on a shared set of activities or events. As in prior sociometric studies of homeless youth, we designated a drop-in center where youth participated in services during approximately 1 month to bound our EBA sample of homeless youth [13].

Homeless youth were recruited every 6 months between January 2012 and February 2013 from one drop-in center. All youth receiving services during the data collection periods were approached and invited to participate in the study. Panel 1 was collected from January 17 to February 10, 2012; 80.2% of youth approached agreed to participate (n = 239). For Panel 2 (July 10 to August 6, 2012), 83.44% of approached youth participated (n = 263). For Panel 3, (January 23 to February 22, 2013), 75.68% of the youth approached agreed to participate (n = 312).

Procedures

Recruiters were present at the agency to approach youth for the duration of service provision hours. The agency has one main entrance where youth sign in for services for the day, ensuring that all youth were approached. Youth new to the agency first completed the agency's intake process before beginning the study to ensure they met the eligibility requirements for the agency (and thus the study). A consistent set of two research staff members was responsible for all recruitment to prevent youth from completing the survey multiple times during each data collection period.

Signed voluntary informed consent was obtained from each youth, with the caveats that child abuse and suicidal and homicidal intentions would be reported. Informed consent was obtained from youth 18 years of age or older and informed assent was obtained from youth 13 to 17 years old. The affiliated institutional review board waived parental consent, because homeless youth younger than 18 are unaccompanied minors without a parent or adult guardian from whom to obtain consent. Interviewers received approximately 40 hours of training, including lectures, role-playing, mock surveys, ethics training, and emergency procedures.

The study consisted of two parts: a social network interview and a computerized self-administered survey. The latter included an audio-assisted version for those with low literacy, and could be completed in English or Spanish. All participants received $20 in cash or gift cards as compensation for their time. The social network interview was conducted by trained research staff members [23]. The research team developed and used an iPad app to collect social network data. Interviewers first explained to youth that they were collecting information about everyone in their social network during the previous month. Participants were asked to name every person they interacted with either face-to-face, on the phone, or in written forms of communication including text messages, emails, or through a social networking site like Facebook, Twitter, etc. After each youth finished nominating alters, the interviewer asked a series of questions regarding the attributes of each alter. Interviewers asked for each alter's first and last name, nickname or street name, visible tattoos, age, race, gender, length known, and if the alter was a relative. The affiliated institutional review board approved all survey items and procedures.

A sociomatrix was created to link participants in the sample. A directed tie from participant i to participant j was recorded if participant i nominated participant j in his or her personal network. Matches were based on first name, last name, alias, race and ethnicity, gender, approximate age, tattoos, and agency attendance. Two independent reviewers made match decisions for all alters between 13 and 39 years old who were not identified as agency staff members. If two distinct youth matched on all information, presence of a third common tie in each personal network was used to assign adjacency. When insufficient descriptive information was available, decisions were based on a series of algorithms that included: (a) interviewer and recruiter field knowledge (through the compilation of field notes following each data collection period); (b) how well the ego knew the alter (e.g., relative, romantic partner, needle sharer, known for at least 1 year) and whether the alter was identified as a client; or (c) via an Microsoft Access database and form that formulaically paired possible matches based on names, visible tattoos, and demographic characteristics. The independent reviewers' decisions were compared for agreement. Discrepant matches were discussed as a group with the independent reviewers and a third reviewer who also served as an interviewer and recruiter during the data collection and led to final match decisions. For the first panel, 389 ties were initially discrepant between the two coders and consensus could not be reached on five (99.991% agreement on possible ties); for the second panel, 208 ties were initially discrepant and consensus could not be reached on two (99.997% agreement on possible ties); and for the third panel, 185 were initially discrepant and consensus could not be reached on two (99.998% agreement on possible ties). These nine ties were coded as 0 (hence a conservative matrix of ties).

Measures

Background characteristics: Race and ethnicity, gender, sexual identity, and current living situation were assessed via self-report. Race and ethnicity was dichotomized as African American, White, Latino, mixed, and other (Asian, Native Hawaiian or Asian Pacific Islander, or American Indian or Alaska Native), with African American as the reference group based on frequency. Dichotomized sexual identity categories were heterosexual, homosexual, bisexual, and questioning, with heterosexual as the reference group. Dichotomized gender included male, female, male-to-female transgender, and female-to-male transgender, with male as the reference group. Current living situation was collapsed into four categories based on 21 questions regarding current living situation. The four categories were unstable or temporary housing (such as couch surfing, hotel, a relative's home, etc.), on the streets (tent, car, bus, etc.), in an emergency shelter, or in a transitional or sober living facility. These four variables were then dichotomized for use as control variables, dummy coding each variable versus all others (given similar frequencies for several of the categories). Recent individual marijuana use was assessed by self-report using the marijuana use item from the Centers for Disease Control and Prevention's [27]. Youth Risk Behavior Survey and dichotomized to indicate using 20 or more times per month based on cutoffs in the literature regarding heavy substance use daily or near daily use [12,28]. Repeaters were calculated with a simple count of individuals that appeared in more than one panel.

Network characteristics: UCINET 6 [29] was used to create measures of network connectivity. For all network measures, an undirected matrix of ties was created from the original directed nominations data. As such, any relationship defined by either a sender or receiver of a nomination was considered a valid relationship.

Degree centrality is a measure of the number of ties to a node, or the number of edges adjacent to a node [30,31,32]. Calculating the degree centrality of each node in the network and turning these values into variables allows examination of minimum, maximum, and average degree centrality in the network and whether behavioural health outcomes are associated with these measures. For the purpose of this analysis, only undirected ties (symmetrised networks) were considered, allowing an examination of the impact of those network ties within the bounds of the homeless network. Calculation of degree centrality allowed for determination of position in the network, or how popular these youth were in the larger homeless network. Betweenness, in this case Freeman's betweenness, measures the property of being on the shortest path between two nodes. Betweenness is used to assess centrality, but more specifically to measure a node's ability to influence the passage of contact and information between actors. Eigenvector centrality measures centrality, but unlike degree centrality it weighs contacts according to the centrality of each peer. It is a weighted sum of all direct and indirect connections, accounting for the entire pattern of connections in the network. Marijuana-using peers were operationalized based on the number of direct ties a given youth had to an alter who self-reported heavy marijuana use.

Data analysis: Data were entered into NetDraw 2.090 [33], and the spring embedder routine was used to generate the network visualizations presented in (Figure 1). Spring embedding is based on the idea that two actors may be thought of as pushing or pulling each other; two points located close together represent actors who have a pull on each other, whereas distant actors push each other apart. The algorithm seeks a global optimum where there is the least stress on the springs connecting actors to one another [34]. For the final multivariate regressions, the network variables were entered into separate models due to issues of multicollinearity between network measures. Due to the overall high rate of marijuana use in the population, correlations were run between network variables, finding significant correlations between these variables. As a result of the generally high levels of marijuana use and interrelatedness of measures, these variables were not added to separate models.

All network variables created in UCINET were exported and merged with self-report data in SAS. The resulting network variables were treated as individual-level characteristics in subsequent regression models. Despite the inherent violation of the assumption of independence of observations in sociometric data, such statistical analyses have become common in applied research [35]. To better understand the effect of node connectivity on participants who were included in multiple panels, each panel was analyzed separately to avoid multiple observations of single individuals or dyadic relationships.

RESULTS

Figure (1) graphically depicts each network for each panel. Visual inspection reveals some notable similarities. At all three time points, the network featured a large number of isolated youth, a smaller number of youth located in dyads and triads, and a large number of youth grouped in a large interconnected component. Table (1) outlines the basic demographic characteristics of each panel over time. Participants were largely heterosexual and male, and the largest racial and ethnic group was African American in each panel. Heavy marijuana use was fairly consistent over time, with 36% to 40% of participants reporting heavy use. Across panels, 29.29% of youth were present in the data across

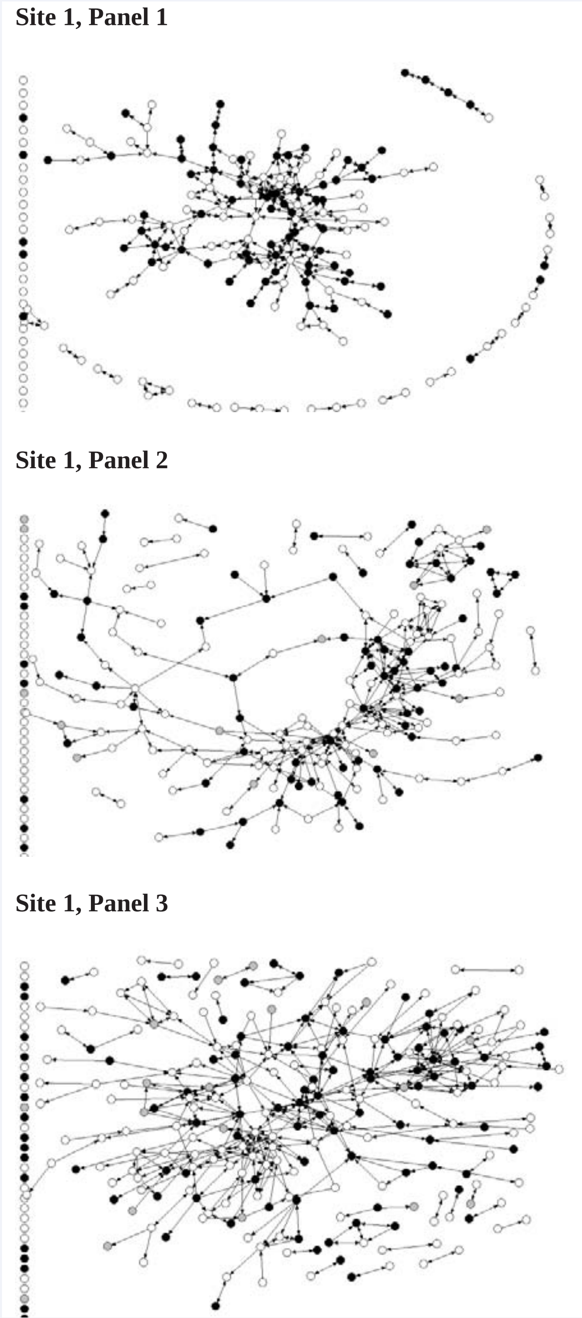

Figure 1 Marijuana use by network. Black dots are heavy marijuana users, white dots are nonusers.

all three waves, with 59.72% repeating more than one panel of data collection, indicating a substantial amount of turnover in the sample over time.

Table (2) describes structural features of the network. Average degree centrality among youth ranged from 2.00 to 2.36, indicating that youth reported approximately two connections to other youth, results that remained consistent over time. Betweenness ranged from 0.14 to 0.27, indicating low levels of individuals' bridging of relationships between other youth in this network. Eigenvector centrality ranged from 0.02 to 0.03, indicating low global connectivity of nodes in the network. Finally, the average numbers of marijuana-using peers ranged from 0.80 to 1.04, indicating that most individuals were affiliated with at least one peer who frequently uses marijuana (more than 20 times a month.

Results of the logistic regression for marijuana use indicate significant associations between network measures and heavy marijuana use in this population. As Table 3 demonstrates with unadjusted odds ratios (*OR*), the association between network measures and heavy marijuana use varied over time, with statistically significant *OR*s for Panel 1 for undirected degree

Table 1: Descriptive statistics over time: Homeless youth, Los Angeles, CA, 2012–13.

	Panel 1	Panel 2	Panel 3
	n = 239	*n* = 263	*n* = 312
	%	%	%
Race			
American Indian or Alaska Native	3.57	1.21	3.64
Asian	0.45	0.44	0.66
Black or African American	41.52	36.44	34.44
Native Hawaiian or Pacific Islander	0.89	0.81	0.33
White	16.52	16.6	22.19
Latino or Hispanic	20.54	22.27	16.23
Mixed	16.52	22.27	22.52
Gender			
Male	64.73	88.35	66.99
Female	33.93	11.65	30.07
Male-to-female transgender	0.89	1.59	1.96
Female-to-male transgender	0.45	0.80	0.98
Sexual orientation			
Homosexual	11.4	9.76	12.66
Bisexual	13.7	13.77	16.67
Heterosexual	72.15	74.49	67.67
Questioning	2.74	1.62	3.00
Age[a]	21.12(2.01)	21.08 (1.88)	21.35 (2.07)
Current living situation			
Unstable or temporary housing	32.27	32.15	36.77
Streets	28.18	20.98	33.84
Emergency or temporary shelter	20.91	15.18	8.56
Transitional living program	5.45	2.68	5.88
Marijuana use during previous 30 days			
0 times	34.55	35.48	27.99
1–2 times	8.64	12.90	9.90
3–9 times	9.55	8.06	13.65
10–19 times	7.27	7.66	9.56
20–39 times	12.73	10.08	7.85
40+ times	27.27	25.81	31.06
Repeaters			
Panels 1 and 2	44.35		
Panels 2 and 3	41.83		
Any panel	52.72		
All panels	29.29		

[a]Figures represent *M* [*SD*].

Table 2: Network position and stability over time: Homeless youth, Los Angeles, CA, 2012–13.

	Panel 1	Panel 2	Panel 3
	M [*SD*]	*M* [*SD*]	*M* [*SD*]
Degree centrality	2.03 [2.48]	2.00 [2.35]	2.36 [2.77]
Betweenness	0.27 [0.64]	0.14 [0.49]	0.25 [0.78]
Eigenvector centrality	0.02 [0.06]	0.03 [0.06]	0.02 [0.05]
Marijuana-using peers	1.03 [1.56]	0.80 [1.34]	1.04 [1.46]

*p< .05. **p< .001.

Table 3: Univariable logistic regression of network position and homophily on heavy marijuana use: Homeless youth, Los Angeles, CA, 2012–13.

	Panel 1		Panel 2		Panel 3	
	OR	**95% CI**	***OR***	**95% CI**	***OR***	**95% CI**
Degree centrality	1.23***	1.09, 1.39	1.10	0.99, 1.23	1.11*	1.02, 1.20
Betweenness	1.62*	1.06, 2.47	1.02	0.61, 1.70	1.22	0.91, 1.63
Eigenvector centrality	31.46	0.42, 999.99	5.24	0.06, 437.59	0.65	0.01, 57.86
Marijuana-using peers	1.48**	1.23, 1.79	1.65**	1.31, 2.08	1.41**	1.19, 1.67

*p< .05. **p< .001.

Table 4: Multivariate logistic regression of network position, number of marijuana-using peers, and control variables on heavy marijuana use: Homeless youth, Los Angeles, CA, 2012–13.

	Panel 1			Panel 2		Panel 3	
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
	OR (95% CI)	*OR* (95% CI)	*OR* (95% CI)	*OR* (95% CI)	*OR* (95% CI)	*OR* (95% CI)	*OR* (95% CI)
Age	1.06 (0.89, 1.27)	1.03 (0.86, 1.24)	1.06 (0.89, 2.77)	0.86 (0.73, 1.01)	0.87 (0.73, 1.03)	0.98 (0.87, 1.11)	0.99 (0.87, 1.12)
White	1.32 (0.56, 3.17)	1.30 (0.54, 3.14)	1.48 (0.63, 1.27)	2.29* (1.08, 4.85)	1.83 (0.83, 4.04)	1.42 (0.78, 2.60)	1.30 (0.71, 2.40)
Male	2.64* (1.23, 5.69)	2.88** (1.31, 6.30)	2.42* (1.15, 5.10)	2.15* (1.07, 4.33)	2.11* (1.03, 4.29)	1.37 (0.76, 2.49)	1.35 (0.74, 2.46)
Nonheterosexual	1.36 (0.64, 2.90)	1.26 (0.59, 2.69)	1.32 (0.63, 2.76)	0.88 (0.44, 1.76)	0.85 (0.41, 1.73)	0.76 (0.42, 1.35)	0.76 (0.42, 1.37)
Living on street	1.85 (0.89, 3.81)	1.64 (0.78, 3.42)	1.80 (0.89, 3.65)	1.27 (0.62, 2.60)	1.28 (0.61, 2.66)	1.76* (1.01, 3.05)	1.72 (0.98, 3.00)
Depression	1.03 (0.98, 1.08)	1.02 (0.98, 1.07)	1.03 (0.98, 1.07)	1.09** (1.04, 1.15)	1.09** (1.03, 1.15)	1.03 (0.99, 1.08)	1.03 (0.99, 1.08)
Degree centrality	1.29** (1.20, 1.50)			1.09 (0.96, 1.23)		1.11* (1.01, 1.22)	
Marijuana-using peers		1.54*** (1.21,1.96)			1.53** (1.19, 1.98)		1.37*** (1.14, 1.63)
Betweeness			1.68* (1.02, 2.77)				

*p< .05. **p< .01. ***p< .001.

centrality (OR) = 1.23; 95% CI = 1.09, 1.39; $p< .001$), betweenness (*OR* = 1.62; 95% CI = 1.06, 2.47; $p< .05$), and number of marijuana-using peers (*OR* = 1.48; 95% CI = 1.23,1,79; $p< .01$). For Panel 2, there were significant results for the number of marijuana-using peers (*OR* = 1.65; 95% CI = 1.31, 2.08; $p< .01$). For Panel 3, there were significant results for undirected degree centrality (*OR* = 1.11; 95% CI = 1.02, 1.20; $p< .05$) and number of marijuana-using peers (*OR* = 1.41; 95% CI = 1.19, 1.67; $p< .01$).

Table (4) shows the results of the multivariable analyses. Controlling for demographic variables and depressive symptoms, the number of marijuana-using peers was consistently and positively associated with increased odds of reporting heavy marijuana use across all panels. Additionally, degree centrality was positively associated with increased odds of heavy marijuana use for Panel 1 (*OR* = 1.29; 95% CI = 1.20, 1.50; $p< .01$) and Panel 3 (*OR* = 1.11; 95% CI = 1.01, 1.22; $p< .05$). Betweenness was positively associated with heavy marijuana use for Panel 1 only (*OR* = 1.68; 95% CI = 1.02, 2.77; $p< .05$). Because of issues of multicollinearity between undirected degree centrality, betweenness, and number of marijuana-using peers in this analysis, these independent variables were analyzed in separate models (Table 4).

DISCUSSION

To our knowledge, this was the first study to examine marijuana use among homeless youth in the context of longitudinal sociometric network data. These data augment prior work that has demonstrated that marijuana use is more frequent among homeless youth who have peers who are also marijuana users [9,14]. The sociometric nature of these data generated several important new insights into how peer processes affect marijuana use among homeless youth.

First, this network of homeless youth represents an open system, lacking stability. Less than a third of the youth remained in this network across all three panels and less than half of the participants remained in the network across either 6-month interval. These findings support other studies that have shown that network ties among homeless youth are often transient and short-lived in nature [36,37]. These data show that these short-lived relationships are partly driven by the instability of the population, the influx of new youth into the network, and the rapid outflow of youth away from this larger network over time.

Second, despite the instability of the network, heavy marijuana users were consistently significantly connected to other heavy marijuana users. This similarity in use across network ties has been seen in other studies, in which substance-using youth are connected to other substance-using youth [38,39,40]. The results of this analysis indicate that heavy marijuana use is an attribute that binds these youth together, even as this network is built and rebuilt over time due to turnover in network membership. This suggests that there are strong selection pressures around marijuana use in this network over time. Indeed, we believe that marijuana use constitutes a sort of social glue that helps to facilitate the creation of short-lived social ties among many homeless youth.

Finally, youth who were more popular were more likely to use marijuana. Furthermore, at most time points, the likelihood of an individual to engage in heavy marijuana use increased as the number of peers to whom that individual was connected increased. Because of the generally high rate of marijuana use in this network, being more connected to other youth, being more popular, or having more marijuana-using peers resulted in higher rates of individual use. These constructs were all highly correlated, often involving the identification of the same alters surrounding a given youth. In these networks, to be a popular youth meant having many friends who use marijuana daily or nearly every day. This augments our understanding of marijuana use beyond what has been seen in egocentric studies, insofar as these data show that popularity equates to high levels of connectivity to habitual marijuana users.

LIMITATIONS

Limitations of this analysis include sampling from one drop-in center, limiting the generalizability of our findings to service-seeking homeless youth. As a result, we cannot address the experiences of all homeless youth with these data. It is important to note, however, that this sample of youth included individuals in emergency shelters and independent living programs and sleeping on the streets, and as such results are generalizable to a wide spectrum of homeless youth. Additionally, with self-reported data, there is the possibility of social desirability bias, because participants may not accurately or completely report substance use behaviours or feel comfortable sharing certain information with interviewers, despite reassurances of confidentiality and a certificate of confidentiality from the U.S. Department of Health and Human Services.

IMPLICATIONS

From the present study, heavy marijuana use seems to be a global network occurrence in this network, and youth who are more popular are also more connected to heavy-marijuana-using peers. This conflation of marijuana use and popularity may reduce the effectiveness of peer-led prevention interventions for marijuana use, because popularity and thus reach as a peer leader in such a model may be inextricably tied to the very marijuana-using patterns we would hope these youth could change. New intervention strategies that may change network ties, that is help lower risk youth to form more ties to other youth who are not using marijuana as heavily may also be an important direction to pursue.

REFERENCES

1. National Alliance to End Homelessness. Homelessness counts. Washington, DC. 2007.
2. Ringwalt CL, Greene JM, Robertson M, Mc Pheeters M.The prevalence of homelessness among adolescents in the United States. Am J Public Health. 1998; 88: 1325–1329.
3. Toro PA. Toward an international understanding of homelessness. J Soc Issu. 2007; 63: 461–481.
4. Bousman CA, Blumberg EJ, Shillington AM, Hovell MF, Ji M, Lehman S, et al. Predictors of substance use among homeless youth in San Diego. Addict Behav. 2005; 30: 1100–1110.
5. Salomonsen SS, Van LJM, Gilroy C, Boyle S, Malberg D, Hopfer C. Correlates of substance use among homeless youth in eight cities. Am J Addic. 2010; 17: 224-234.
6. Tyler KA, Melander LA. Child abuse, street victimization, and substance use among homeless young adults.Youth & Society. 2013; 47: 502–519.
7. Baer JS, Ginzler JA, Peterson PL. DSM-IV alcohol and substance abuse and dependence in homeless youth. J Stud Alc. 2003; 64: 5–14.
8. Merrill JC, Kleber HD, Schwartz M, Liu H, Lewis SR. Cigarette, alcohol, marijuana, other risk behaviors, and American youth. Drug Alcohol Depend.1999; 56: 205–212.
9. Rice E, Milburn NG, Monro W. Social networking technology, social network composition, and reductions in substance use among homeless adolescents. Prev Sci. 2011; 12: 80–88.
10. Wenzel SL, Tucker JS, Golinelli D, Green HD, Jr, Zhou A. Personal network correlates of alcohol, cigarette, and marijuana use among homeless youth. Drug Alcohol Depend. 2010; 112: 140–149.
11. Harvey MA, Sellman JD, Porter RJ, Frampton CM. The relationship between non-acute adolescent cannabis use and cognition. Drug Alcohol Rev. 2007; 26: 309–319.
12. Arnone D, Barrick TR, Chengappa S, Mackay CE, Clark CA, Abou-Saleh MT. Corpus callosum damage in heavy marijuana use: Preliminary evidence from diffusion tensor tractography and tract-based spatial statistics. Neuroimage. 2008; 41: 1067–1074.
13. Rice E, Barman-Adhikari A, Milburn NG, Monro W. Position-specific HIV risk in a large network of homeless youths. Am J Public Health. 2012; 102: 141–147.
14. Baron SW. Street youths and substance use: The role of background, street lifestyle, and economic factors. Youth & Society. 1999; 31: 3–26.
15. Green HD Jr, de la Haye K, Tucker JS, Golinelli D. Shared risk: Who engages in substance use with American homeless youth? Addiction. 2013; 108: 1618–1624.
16. McMorris BJ, Tyler KA, Whitbeck LB, Hoyt DR. Familial and “on-the-street” risk factors associated with alcohol use among homeless and runaway adolescents. J Stud Alc. 2002; 63: 34–43.

17. Whitbeck LB, Hoyt DR. Nowhere to grow: Homeless and runaway adolescents and their families.1999.

18. Rice E, Milburn NG, Rotheram-Borus MJ, Mallett S, Rosenthal D. The effects of peer group network properties on drug use among homeless youth. Am Behav Sci. 2005; 48: 1102–1123.

19. Marsden PV. Network data and management. Ann Review Sociol.1990; 16: 435–463.

20. Yang C, Latkin C, Muth SQ, Rudolph A. Injection drug users' involvement in drug economy: Dynamics of sociometric and egocentric social networks. Connect (Tor). 2013; 33: 24–34.

21. Rice E, Rhoades H. How should network-based prevention for homeless youth be implemented? Addiction. 2013; 108: 1625–1626.

22. Whitbeck LB. Mental health and emerging adulthood among homeless young people. Psychology Press. 2009.

23. Rice E. The positive role of social networks and social networking technology in the condom-using behaviors of homeless young people. Public Health Rep. 2010; 125: 588–595.

24. Rice E, Milburn NG, Rotheram-Borus MJ. Pro-social and problematic social network influences on HIV/AIDS risk behaviours among newly homeless youth in Los Angeles. AIDS Care. 2007; 19: 697–704.

25. Marsden PV. Recent developments in network measurement. Models and methods in social network analysis. 2005: 8–30.

26. Freeman LC, Webster CM. Interpersonal proximity in social and cognitive space. Social Cognition. 1994; 12: 223–247.

27. Centers for Disease Control and Prevention. National YRBS data users manual. 2009.

28. Whitlow CT, Liguori A, Livengood LB, Hart SL, Mussat-Whitlow BJ, Lamborn CM, et al. Long-term heavy marijuana users make costly decisions on a gambling task. Drug Alcohol Depend. 2004; 76: 107–111.

29. Borgatti SP, Everett MG, Freeman LC.UCINET for Windows: Software for social network analysis. 2002.

30. Borgatti SP. Centrality and AIDS. Connections. 1995; 18: 112–115.

31. Freeman LC. Centrality in social networks: Conceptual clarification. Social Networks. 1978; 1: 215–239.

32. Otte E, Rousseau R. Social network analysis: A powerful strategy, also for the information sciences. J Inf Sci. 2002; 28: 441–453.

33. Borgatti SP. NetDraw: Graph visualization software. Harvard, MA: Analytic Technologies. 2002.

34. Freeman LC. Visualizing social networks. JOSS. 2000; 1: 1.

35. Scott J, Carrington PJ. The Sage handbook of social network analysis. Sage. 2011

36. Barczyk AN, Thompson SJ, Rew L. The impact of psychosocial factors on subjective well-being among homeless young adults. Health Soc Work. 2014; 39: 172–180.

37. Bender K, Thompson SJ, McManus H, Lantry J, Flynn PM. Capacity for survival: Exploring strengths of homeless street youth. Child Youth Care Forum. 2007; 36: 25–42.

38. Andrews JA, Tildesley E, Hops H, Li F. The influence of peers on young adult substance use. Health Psychol. 2002; 21: 349–357.

39. Brechwald WA, Prinstein MJ. Beyond homophily: A decade of advances in understanding peer influence processes. J Res Adolesc. 2011; 21: 166–179.

40. Rice E, Milburn NG, Rotheram-Borus MJ, Mallett S, Rosenthal D. The effects of peer group network properties on drug use among homeless youth. Am Behav Sci. 2005; 48: 1102–1123.

Cite this article

Rice E, Yoshioka-Maxwell A, Rhoades H, Winetrobe H, Petering R, et al. (2017) Population-Level Network Structure over Time and Marijuana Use among Homeless Youth. J Subst Abuse Alcohol 5(1): 1052.