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Social network and census tract-level influences on substance use among emerging adult males: An activity spaces approach

Crystal Gibson, MPH¹, Lauren Perley, MA¹, Jonathan Bailey¹, Russell Barbour, PhD¹, and Trace Kershaw, PhD¹

¹Yale School of Public Health, 135 College St., New Haven, CT 06510

Abstract

Social network and area level characteristics have been linked to substance use. We used snowball sampling to recruit 90 predominantly African American emerging adult men who provided typical locations visited ($n=510$). We used generalized estimating equations to examine social network and area level predictors of substance use. Lower social network quality was associated with days of marijuana use ($B=-0.0037$, $p<0.0001$) and problem alcohol use ($B=-0.0050$, $p=0.0181$). The influence of area characteristics on substance use differed between risky and non-risky spaces. Peer and area influences are important for substance use among men, and may differ for high and low risk places.

Keywords

Activity spaces; emerging adults; alcohol; marijuana; social networks

Introduction

Emerging adulthood (age 18-25) is a time when men seek employment and become independent from family, providing more opportunity for risk behavior. Alcohol and substance use are common among emerging adults, with estimates in the US near 70% for past year alcohol use and 43% for illicit drug use.¹ Substance abuse (e.g., substance use associated with impairment or distress at work or school, interpersonally, or with legal implications)² may result in various adverse outcomes, including mortality, unsafe sex, poor mental health, and crime.³⁻⁷ In addition, heavy use early in life may lead to subsequent substance abuse or dependence (e.g. physical tolerance of a substance or inability to control substance use).^{2,3,8} Males are particularly susceptible to problems with alcohol and substances and are at greater risk of becoming regular alcohol and illicit drug users and develop substance abuse and dependence.^{1,7} These problems are striking for minority men. While some studies indicate that black men are less likely to use substances compared to white men,⁹⁻¹¹ there is some evidence that black men may be more likely to experience problems with substances—particularly alcohol—compared to white men.^{11,12} Importantly,

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the black-white disparity among men may be attenuated when adjusting for socioeconomic measures (e.g., employment, household income, education) and other demographics.¹² These studies underscore the importance of additional studies of substance use among emerging adult minority men while incorporating socioeconomic measures.

Use of substances such as marijuana and alcohol has been linked to peer and environmental characteristics. Socialization theory suggests that substance using peers increase the risk an individuals' use of illicit drugs or alcohol by social learning.¹³ Consequently, young adults who belong to social networks with higher concentrations of alcohol and drug users are more likely to use alcohol and drugs themselves.^{3,7,8,14-17} For example, one study found that individuals are 50% more likely to drink alcohol if one of their social network members drinks.¹⁸ Other studies have shown that social networks influence drug use, including tobacco and marijuana.^{8,19-22} The composition and qualities of those social networks (e.g., how many members of the network are substance using and how much influence do specific members have on an individual's behavior) may be particularly important during late adolescence and young adulthood as individuals spend more time in peer contexts and less time at home.²³

Negative area-level characteristics, including poverty and crime, have also been linked to greater alcohol and drug use.²⁴⁻²⁶ These characteristics may influence substance use via different pathways. Neighborhood stress-based frameworks posit that these types of neighborhood features act as chronic stressors; in this context, individuals may use alcohol or illicit drugs to alleviate or cope with these stressors.²⁷ However, it is important to note that the evidence for these associations is mixed; while some studies support this theory and show greater alcohol and drug use in areas of low socioeconomic status and high crime, others show greater substance use in areas with more socioeconomic advantage.²⁸⁻³⁰ Environmental structural theories suggest that physical features of the environment, such as easy access to alcohol outlets, enable risky behaviors.^{17,31} A recent systematic review found a modest association between alcohol outlet density and higher odds of heavy alcohol consumption, though findings were varied across studies.³² Studies specifically targeting adolescents to examine the relationship between alcohol use and alcohol outlet density have found greater binge or excessive drinking in geographic areas with higher densities of alcohol outlets^{29,33,34} suggesting that community availability of alcohol is important in understanding drinking patterns in populations that may have limited access to alcohol. In emerging adult social networks, there may be members of the network of age to purchase alcohol, which may also influence alcohol use in younger members of the network. Availability of alcohol may also influence drug use in emerging adults. A recent study found a decrease in marijuana use with increasing distance to the nearest off-premise alcohol outlet (e.g., (retailers selling alcohol for consumption in a place other than the retail location)).³⁵ Exploration of area-level characteristics that operate on both pathways is important in understanding substance use among emerging adults.

In addition, exploration of features of the environment that may be protective against substance use is important. Access to places for recreational purposes or spiritual and social support may be protective against substance use via stress-buffering mechanisms. In one study, places identified by substance-using adolescents as risky were further from churches

and recreation centers with programs for adolescents.²⁰ Further, Stockdale reported that neighborhood assets such as churches may buffer the risk of developing severe alcohol or drug disorders.²⁷ Other work has documented religiosity as a buffer to stress and protective against substance use; consequently, the role of churches in the community could have a positive influence on drug and alcohol behaviors.^{36,37} Further, the presence of neighborhood parks may be considered community assets that provide opportunities for social interaction and improve psychosocial health, which could be protective against substance use.^{38,39}

Brofenbrenner's ecological model for human development^{40,41} guided the selection of variables used to examine the influence of social and environmental factors on marijuana and alcohol use in a sample of emerging adult men. This framework emphasizes the importance of complex interactions between individuals and the people, objects, and situations encountered in different environmental contexts.^{40,41} Mason and colleagues have applied this framework in previous work examining activity spaces (e.g., places individuals travel to routinely) and substance use among adolescents.^{8,19} Their work has shown differences in the composition of social networks and proximity to negative aspects of the environment (e.g., crime) related to substance use, suggesting that different contexts or settings may interact to influence individuals' behavior.^{8,19,20}

We chose a variety of measures that may promote or protect against substance use among emerging adult men. Measures were chosen due to empirical links to alcohol or marijuana use (e.g., income, crime, police, alcohol outlets, and churches)^{20,27,36,42,43} theoretical links to alcohol or marijuana use (e.g., parks),^{38,39} or places that emerged while talking with emerging men about the places they spend time in (e.g., libraries).

The present study expands on previous work by measuring social network and environmental influences at multiple activity spaces. A significant limitation in many previous studies examining neighborhood context and substance use is the inclusion of one or few locations, often home residence.^{8,15,19,20,43} Previous work indicates that neighborhood characteristics beyond home residence may have more of an influence on risk behavior than neighborhood characteristics of home residence, demonstrating our need to expand the notion of how geographical context may influence health.^{43,44} For example, Mennis and Mason reported that substance use was not associated geographic features of adolescents' home locations; in contrast, neighborhood features such as further distance to police stations and more violent crime were associated with substance use at non-home locations.⁴³ Incorporating multiple locations may be particularly relevant for emerging adults who may spend less time at home and more time in peer contexts during this period.²³ Utilizing activity spaces approach has been identified by Mason and colleagues as important in advancing our understanding of how different social and geographical contexts contribute to unique risks at different activity spaces.^{8,19,20} To our knowledge, this is the first study to consider all activity spaces identified by participants, which allows us to capture the full mobility of individuals while taking into account fluid social networks and neighborhood contexts.

We utilized an activity spaces approach to examine alcohol and drug use among emerging adult men. Specifically, we aimed to 1) assess the influence of social networks and census

tract level characteristics (socioeconomic and built environment characteristics) as independent predictors of substance use, 2) examine whether activity spaces characterized as risky or non-risky differ by social network influence and census tract level characteristics, and 3) assess whether these associations differ for risky and non-risky locations.

Method

Procedures

The study included young men participating in a longitudinal study of social networks, health behavior and health outcomes among emerging males in New Haven, CT. The recruitment process began with use of epidemiologic and census data to identify neighborhoods with high rates of poverty, crime, and negative health outcomes. Outreach workers went to these areas and mapped locations within these neighborhoods that were frequented by young men. Snowball sampling was used to recruit friends of participants. Inclusion criteria for all participants included: (a) male gender; (b) age 18-25; (c) English-speaking; (d) heterosexual.

Data were collected at 3 time points: baseline (Time 1), 3 months after baseline (Time 2), and 6 months after baseline (Time 3). Due to sampling methods, participants were enrolled as they were identified by a social network member. Baseline assessments occurred from March 2011 to September 2013. During the baseline appointment, research staff obtained written informed consent. Participants completed structured interviews via audio computer-assisted self-interviews (ACASI) as well as audio-recorded face-to-face interviews with trained research staff. Participation was voluntary and confidential, and all procedures were approved by the Yale University Human Investigation Committee. Participants were remunerated a minimum of \$150 and a maximum of \$300 for time and effort.

Demographic variables were collected at the baseline visit (Time 1). Activity space information was assessed either 3 months (Time 2) or 6 months (Time 3) following the baseline visit. Predictors and outcomes were assessed at the same time point the activity space exercise was completed.

Activity spaces and mapping information was assessed using techniques adapted from Mason and colleagues.^{8,19,20} This information was used to 1) identify the spatial location of each activity space in order to link each location to census-tract level predictors, and 2) to classify each space as risky or non-risky for use as outcomes during data analysis. Participants were instructed to list all locations visited in a typical week. After obtaining a complete list of locations, participants were asked the following about each place: days per week visited, whether visited during the week or weekend, time of day visited (e.g., day or night), and members of their social network who also spend time at the location. In addition, participants were asked if they use alcohol or drugs at each location. Further questions were asked regarding frequency of use, alcohol and drug use by friends, and features of each location that facilitates each behavior. No participant endorsed hard drug use (e.g., heroin, cocaine) during the activity spaces exercise; therefore we focused our drug use outcomes on the use of marijuana.

Once information was obtained about participants' activity spaces, the website MapFab⁴⁵ was used to drop a place marker for each location on a map. Participants were instructed to provide addresses when possible, or, in the absence of addresses, identify cross streets or landmarks to pinpoint the location of each activity space. Individual maps were exported to Google Earth,⁴⁶ which was used to extract geographic coordinates for each activity space, which were used to identify and link to census tracts.

Measures

Demographic variables—Participants provided their age at the time of the activity spaces mapping. Race, household income (defined as total income of all members living in the same household as the participant), and education were collected during each participant's initial visit. Household income and education were reported as continuous values.

Predictors—*Network quality* was based on a measure of negative-positive network influence adapted from Mason and colleagues.^{8,19,20} Network quality was assessed separately for each activity space for all participants and incorporated network members' participation in alcohol or marijuana use and influence from members in the same network. Specific components of the network quality score are as follows:

Network members at each location: Participants indicated which network members they spend time with at each location.

Classification of network members as substance users: For each network member present at each activity space, participants indicated whether those network members participated in alcohol or marijuana use at each location. Network members received a score of either -4 (if he was a substance user) or +4 (if he was a substance non-user).

Influence of network members: To assess positive influence, participants were asked whether each network member present at the activity space “tries to get me to do the right thing” (range 0 to 4, with 0 indicating no attempt to influence and higher numbers indicating more positive influence). To assess negative influence, participants were asked whether each network member present at the activity space “tries to get me to do what feels good even if there may be consequences” (range 0 to -4, with 0 indicating no attempt to influence lower numbers indicating more negative influence).

Perceived closeness of network members: To assess closeness of network members, participants were asked “how close are you with network member?” for each network member present at the activity space. Perceived closeness ranged from 1 to 7, with a score of 7 indicating more perceived closeness.

Calculation of network quality: Substance use, positive influence, and negative influence scores were summed for each network member such that each network member score ranged from -8 to +8. A total score for each activity space was calculated by summing the scores for all network members listed at that location weighted by the perceived closeness of the participant with the network member. Activity spaces with no network members present

received a zero, indicating a neutral network quality. Higher network quality scores indicated a more positive network quality, whereas lower network quality scores indicated more negative network quality.

Census tract level characteristics included built environment (physical, human-made features of the environment, including infrastructure, structures, and businesses), socioeconomic, and crime characteristics. Built environment characteristics included off-premise alcohol outlets, police stations, churches, libraries and parks. Google Earth was used to search for each category of built environment features and obtain geographic coordinates for each activity space. This is an attractive method, as it is not resource-intensive and has been shown to be reliable for street level characteristics implicated in health outcomes such as food outlets and liquor stores.⁴⁷ Google Earth is updated on a continuous rolling basis. All data is no more than 3 years old, and is usually accurate within a one year time frame.⁴⁸ Half a mile buffers were computed around each activity space, and a count of all built environment characteristics by category was obtained. Similar distances have been used in previous studies, as a half a mile is a walkable distance in which individuals which may facilitate interaction with the environment.³⁴ Buffers were constructed as straight-line distance buffers. Socioeconomic characteristics included median household income, percent unemployment, percent owner-occupied housing, and the EASI Total Crime Index. The EASI Total Crime Index is a composite crime variable that includes murder, forcible rape, robbery, aggravated assault, burglary, larceny and motor vehicle theft.⁴⁹ Violent crimes are given greater weights in the computed variable, and higher values indicate greater crime. The national average for the EASI Total Crime Index is 100. Simply Map⁵⁰ was used to obtain data for median household income, unemployment, and crime at the census-tract level. SimplyMap's web-based application provides downloadable shapefiles at various levels of geography (e.g., state, county, or census tract) derived from the US Census Bureau.⁵⁰ Connecticut census-tract level information for the 2010 Census was used for variables obtained through SimplyMap.

Outcomes—*Problem alcohol use* was assessed with the 3-item version of the Alcohol Use Disorders Identification Test (AUDIT). Previous studies have indicated that the 3-item AUDIT is comparable to the longer 10-item AUDIT in detecting problematic alcohol use behavior.⁵¹ Participants were asked questions regarding frequency of alcohol consumption, amount of alcohol consumption on a typical day of drinking, and how often six or more alcoholic beverages are consumed in one sitting. Response choices for each item ranged from 0 to 4. A total problem alcohol use score was computed by summing the responses for the three items, and ranged from 0 to 12 with higher scores indicating more problematic alcohol consumption.

Days of marijuana use was included as a continuous variable indicating the number of days the participant used marijuana within the last month.

Multiple daily use of marijuana was included as a dichotomous variable indicating whether or not the participant endorsed typically using marijuana 2 or more times per day.

Risky spaces were classified based on information collected during the activity spaces activity. Activity spaces were classified as *risky* if marijuana was used by the participant at that location or if the participant endorsed alcohol use at that location and reported drinking more than 5 alcohol drinks when drinking at that location, which is consistent with the definition of binge drinking.^{6,52} All other locations were classified as *non-risky*. Risky spaces were further dichotomized into *risky alcohol spaces* and *risky marijuana spaces*. Spaces that were classified as *risky alcohol spaces* as well as *risky marijuana spaces* were classified as locations of *extreme high risk*, whereas all others were classified as *not extreme high risk*.

Data Analysis

Descriptive statistics were generated for demographic, activity space, and outcome variables. Next, we conducted multivariate regression to assess spatial and network influences on alcohol and drug use controlled with individual characteristics known to be associated with substance use. Continuous predictors and outcomes were standardized and separate multivariable models were generated for alcohol and marijuana use and risky space indicators using Generalized Estimating Equations (GEE). The data were organized such that each activity space was its own row, with multiple locations per participant. The total rows was equal to the total number of locations identified by participants, which is equivalent to GEE analyses using multiple assessments nested within individuals. The dependence of the data was then modeled using GEE analysis so that the correlated nature of the data (e.g., multiple locations frequented by participants) was accounted for in the analysis.^{53,54} While the AUDIT followed a normal distribution, the number of days of marijuana use was not normal. GEE is robust to non-normal data and is appropriate for both normal and non-normal distributions.^{53,54} The models controlled for number of network members present at each activity space and individual sociodemographic factors (age, income, education, race/ethnicity) that were significant ($p < 0.05$). Controlling for individual factors allowed us to examine social network and census tract characteristics that may influence substance beyond individual characteristics related to substance use. Controlling for the number of network members present at each activity space allowed us to obtain a measure of relative impact of peer influence. To determine whether risky activity spaces moderated the effect of the predictors on alcohol and marijuana outcomes, a risky space by predictor term was added to the models one at a time. To interpret the nature of any interactions simple effects were conducted.

Two maps were created: one showing a visual display of risky and non-risky activity spaces, and one showing risky space clusters. Clusters of high and low risky spaces were examined using the Getis-Ord Gi statistic algorithm in ArcMap 10.2.⁵⁵ This statistic provides a graphical display of the distribution of risky spaces by identifying clusters of points with values higher in magnitude than you might expect to find by random chance.⁵⁵ The Gi statistic is based on a Z score which represents the statistical significance of clustering. We identified statistically significant spatial clusters of high values (hot spots) using this metric and visually identified areas of uniform p values. All statistical analyses were performed using SAS 9.3 while spatial computations and visualizations were performed using ArcGIS 10.2. All point locations for final maps were randomly offset by half a city block for

confidentiality and privacy purposes. Offsets were performed by converting the activity spaces to graphics and nudging them within ArcGIS to obscure the original locations.

Results

The sample consisted of 90 emerging adult males (Table 1). Participants were predominantly African American (77%) or Hispanic (18%), while the remaining participants were White (5%). The mean age was 20.57 (SD=1.97) while the mean education was 13.00 years (SD=2.02). The mean household income was \$20,428 (SD=\$25,181).

Past year alcohol use was endorsed by 80% (n=72) of the participants and among all participants the mean problem alcohol score was 3.56 (SD=2.66). Lifetime marijuana use was endorsed by 77% (n=69) of the participants, and among all participants the mean number of days of marijuana use in the last month was 11.47 (SD= 12.58). Sixty-three (70%) of participants endorsed marijuana use in the past month. Thirty-five (39%) participants reported using marijuana more than one time per day.

Participants identified 510 activity spaces of which 107 (21%) were classified as risky. There was a mean of 5.86 spaces (SD=1.98) per participant. Figure 1 shows the identified activity spaces and risky and non-risky activity spaces, while characteristics of the activity spaces are shown in Table 2. Activity spaces were located in 73 census tracts, primarily within the city of New Haven (n=390 or 78%). The mean number of peers present at each space was 2.00 (SD=2.04) and the mean network quality score was 43.75 (SD=89.63). Number of physical built environment features within 0.5 miles of each activity space ranged from a mean of 0.49 features (libraries, SD=0.72) to 9.99 (churches, SD=8.48). The mean crime index for the activity spaces was 65.95 (SD=55.93) and the median household income was \$48,008 (SD=\$ 19,979).

Table 3 shows the results of models examining alcohol and marijuana use as outcomes using GEE. Lower network quality at the activity spaces was significantly associated with a higher number of days of marijuana use (B=-0.0037, 95%CI=-0.0056, -0.0019, p<0.0001), use of marijuana more than one time per day (B=-0.0073, 95%CI=-0.0113, -0.0034, p=0.0003), and higher scores for problem alcohol use (B=-0.0050, 95%CI=-0.0092, -0.0009, p=0.0181). Higher percent owner-occupied housing was associated with use of marijuana more than one time per day (B=0.0063, p=0.0379). No other predictors were significantly associated with marijuana or alcohol use.

Table 4 shows the results of models examining risky spaces (total), risky alcohol spaces and risky marijuana spaces as outcomes using GEE. Lower network quality was associated with risky spaces (defined as risky alcohol or marijuana use at the space; B=-1.1786, 95%CI=-1.5184, -0.8388, p<0.0001). A lower count of libraries within a 0.5 mile radius of activity spaces was associated with risky spaces (B=-0.3904, 95%CI=-0.7278, -0.0530, p=0.0233). When examining risky marijuana spaces separately, lower network quality was associated with risky marijuana spaces (B=-1.1076, 95%CI=-1.4351, -0.7800, p<0.0001). When examining risky alcohol spaces separately, lower network quality was associated with risky activity spaces (B=-0.5126, 95%CI=-0.9293, -0.0960, p=0.0159). Finally, when

examining activity spaces that were classified as extremely high risk, lower network quality was associated with extremely high risk spaces ($B=-0.5089$, 95%CI= -0.8965 , -0.1213 , $p=0.0101$). Extremely high risk spaces were associated with a lower count of police stations ($B=-0.9780$, 95%CI= -1.7393 , -0.2166 , $p=0.0118$), a lower count of parks ($B=-1.1380$, 95%CI= -2.1499 , -0.1261 , $p=0.0275$), and a higher count of alcohol outlets ($B=1.2556$, 95%CI= 0.5847 , 1.9266 , $p=0.0002$).

Next, we examined risky space and predictor interactions for alcohol and marijuana outcomes. No significant interactions for risky space by marijuana use more than one time per day were observed. There was a significant interaction between risky space and unemployment for number of days of marijuana use ($B=0.0026$, 95%CI= -0.0002 , 0.0051 , $p=0.0356$). Simple effects showed more unemployment in non-risky spaces was related to greater number of days of marijuana use ($B=0.0020$, 95%CI= 0.0005 , 0.0035 , $p=0.0097$) whereas unemployment in risky spaces was not related to greater number of days used marijuana ($B=-0.0002$, 95%CI= -0.0010 , 0.0006 , $p=0.6512$). There was a significant interaction between risky space and number of police stations for number of days of marijuana use ($B=0.0045$, 95%CI= 0.0004 , 0.0086 , $p=0.0316$). Simple effects showed that a higher number of days used marijuana was marginally related to a higher number of police stations in non-risky spaces ($B=0.0024$, 95%CI= -0.0002 , 0.0049 , $p=0.0655$) whereas there was no relationship between number of police stations and marijuana use in risky spaces ($B=-0.0008$, 95%CI= -0.0021 , 0.0005 , $p=0.2152$). There was a significant interaction between risky space and the count of off-premise alcohol outlets for number of days of marijuana use ($B=0.0030$, 95%CI= 0.0001 , 0.0059 , $p=0.0442$). However, simple effects did not show significant relationships between risky and non-risky spaces and number of alcohol outlets for number of days of marijuana use. Finally, there was a significant interaction between unemployment and risky space for problem alcohol use ($B=-0.0047$, 95%CI= -0.0093 , -0.0001 , $p=0.0442$). Simple effects showed that less unemployment around non-risky spaces was marginally related to more problem alcohol use ($B=-0.0037$, 95%CI= -0.0075 , 0.0001 , $p=0.0564$) whereas there was no relationship between unemployment and problem alcohol use in risky spaces ($B=0.0005$, 95%CI= -0.0083 , 0.0022 , $p=0.5630$).

Discussion

Our study provides evidence that peer and area-level features of activity spaces influence alcohol and marijuana use among a sample of mostly minority emerging adult men. Our results extend the work of Mason and colleagues by exploring these associations at multiple activity space identified by individual participants, which is particularly important for the emerging adult men who participated in our study, as they visit many different places during a typical week. Consistent with previous work utilizing similar methods, the quality of social networks at activity spaces was associated with alcohol and marijuana use.^{8,19,20} When examining simple effects of neighborhood level characteristics we did not find a relationship between substance use and neighborhood level indicators. However, our results suggest that neighborhood level influences on substance use may be influenced by the characteristics of the space, namely whether the space is a location for high risk alcohol or marijuana use. Higher unemployment and higher numbers of police stations in non-risky activity spaces were related to greater marijuana use. The unemployment finding was unexpected given

prior literature suggesting that neighborhood socioeconomic stressors may lead to greater substance use.^{25,56} We expected higher unemployment to be associated with substance use in risky spaces, as these were spaces where risky substance use occurred. However, Karriker-Jaffe's systematic review of area-level socioeconomic status and substance use suggested that neighborhood disadvantage—which is related to socioeconomic indicators—is more related to illicit substances other than marijuana and heavy alcohol consumption.²⁸ It is possible that area-level influences are different for marijuana. More work is needed to explore these nuances. Undoubtedly, our results suggest complexity in how geographic characteristics influence substance use, and contribute to a mixed literature that has not come to a consensus on how area-level socioeconomic characteristics influence the use of drugs and alcohol.^{8,24-26,29,30,42,57}

When examining predictors of risky activity spaces, lower network quality was associated with risky spaces, suggesting that combinations of substance-using peers who are perceived to have a negative influence on the individual may promote substance use. This finding was true regardless of whether the risky space was a risky alcohol space or a risky marijuana space. In addition, fewer libraries were associated with risky spaces. Many study participants included libraries as part of their activity spaces, suggesting that libraries may be a type of recreational location that may protect against substance use. Fewer parks were associated with extremely high risk spaces. Our results for area-level measures support structural features of the built environment may be related to risky substance use in emerging adult men.³⁹ For example, few recreational spaces, such as parks, may limit more positive community and social interactions that could protect against substance use. In contrast, fewer police stations and high access to alcohol may facilitate substance use in young men by reducing the perceived risk of substance use, as fewer police may be present to monitor alcohol consumption.⁵⁸

While we expected to observe more associations with other area-level indicators, particularly socioeconomic indicators, features of our study may have contributed to null findings. Our sample was small, which led to a relatively small number of locations overall as well as a small number of risky alcohol and marijuana locations. The small number of activity spaces may have limited our ability to detect statistically significant associations with predictors and outcomes. In addition, the sample size prevents generalizability to a larger emerging male population, as we only included 90 young men from one urban city. Another important caveat to note is that our data were cross-sectional, which limits inferences about causality between our predictors and substance use. The association between substance use and social network and geographic influences may be bidirectional; while our framework fit within the context of peer socialization, social networks may be constructed due to peer selection (e.g. individuals select peers with desired behaviors) or a combination of both processes.¹³ Census-tract level features may operate similarly—individuals may be selective in the environments they choose to frequent, such as those that may enable substance use, or features of their environments may influence their behaviors via stress or other pathways. Future work incorporating event-based approaches into longitudinal designs could provide important information addressing this gap.

Further, our analyses were limited to close peers that spend time together in their activity spaces. Consequently, we have no information about other individuals who may also be present at various activity spaces and influence substance abuse behavior. We also only recorded primary social network membership for each participant, which prevents us from quantifying the overlap between individuals from different social networks. We also did not capture the amount of time spent at each activity space; consequently, each activity space was given the same weight in our analyses. It would be beneficial to examine differential effects of area and social network measures by a time metric. In addition, the time of data collection did not overlap with area-level measures from the US Census, which could affect our results. As Google Earth is updated relatively frequently, built environment features should reasonably reflect the geographic context of the participants' locations; however, there is a possibility that the time periods did not overlap and we over or underestimated built environment features using this method. Finally, we conducted multiple comparisons without including a statistical correction (e.g., Bonferroni correction). However, due to the small sample size we expected Type II error to be more of an issue than Type I error.

Despite these limitations, our study had numerous strengths including the exploration of the unique interaction of peer and neighborhood influences on a high risk sample, and expanding the notion of neighborhood influences by including all routine activity spaces used by emerging adult males. Understanding how social networks and neighborhood-level influences confer risks is important in elucidating relationships between these factors and substance use in young people. Event-based approaches provide another layer of context that may aid in understanding how risk changes with different combinations of these factors. It also enables detection of geographic clusters of activity spaces for this population, which may help in targeting interventions to reduce risk for poor outcomes related to substance use. Future work would benefit in integrating perceptions of neighborhood level indicators, such as perceived safety, accessibility to alcohol, and neighborhood deprivation, as individual-level experiences and beliefs about their environments may be important in understanding patterns of substance use.

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Highlights

1. Peer behavior within social networks influences substance use among emerging minority men
2. Neighborhood factors may influence behavior differently for risky versus non-risky spaces
3. Including multiple activity spaces is an important tool in elucidating these relationships

Figure 1. Risky and non-risky activity spaces

Figure 2. Risky space cluster using the Getis-Ord Gi statistic

Table 1
Participant demographics and characteristics

	Mean (SD)	N (%)
<i>Demographics</i>		
Age	20.57 (1.97)	
Education (years)	13.00 (2.02)	
Income ^a	\$20,428 (\$25,181)	
Race		
White		5 (5)
African American		69 (77)
Hispanic		16 (18)
<i>Outcomes</i>		
Alcohol use		72 (80)
Problem alcohol score	3.56 (2.66)	
Marijuana use		69 (77)
Multiple daily marijuana use		35 (39)
Days marijuana use	11.47 (12.58)	

^aMissing for 14 participants

Table 2
Activity spaces, substance use outcomes, and census tract characteristics

	Mean (SD)	N (%)
<i>Activity spaces</i>		
Number of activity spaces	5.86 (1.98)	
Number of alters present	2.00 (2.04)	
Network quality score ^a	43.75 (89.63)	
Risky activity spaces ^b		107 (21)
Risky alcohol spaces		25 (5)
Risky marijuana spaces		96(19)
Extreme high risk spaces		14 (3)
<i>Substance use outcomes</i>		
Alcohol use		72 (80)
Problem alcohol score	3.56 (2.66)	
Marijuana use		69 (77)
Multiple daily marijuana use		35 (39)
Days marijuana use	11.47 (12.58)	
<i>Census level data</i>		
Median household income	\$48,008 (\$19,979)	
Owner occupied housing (percent)	32.54 (23.70)	
Unemployment (percent)	15.39 (7.68)	
Crime index	65.94 (55.93)	
<i>Count of places within 0.5 miles of activity spaces</i>		
Police stations	0.78 (0.83)	
Parks	0.85 (0.96)	
Churches	9.99 (8.48)	
Aries	0.49 (0.72)	
Off-premise alcohol outlets	2.98 (2.29)	

^aMissing for 4 activity spaces

^bMissing for 9 activity spaces

Table 3

Predictors of risky marijuana and alcohol use

	Model 1: Number of days smoked marijuana		Model 2: Use of marijuana more than one time per day		Model 3: Risky consumption of alcohol	
	B	95% CI	B	95% CI	B	95% CI
% Unemployed	0.0013	-0.0002, 0.0027	0.0012	-0.0019, 0.0042	-0.0022	-0.0058, 0.0015
% Owner-occupied housing	0.0028	-0.0009, 0.0064	0.0063*	0.0004, 0.0122	-0.0005	-0.0069, 0.0060
Median household income	-0.0008	-0.0045, 0.0028	-0.0038	-0.0102, 0.0025	-0.0023	-0.0090, 0.0043
Crime index	0.0001	-0.0016, 0.0017	0.0012	-0.0017, 0.0040	-0.0017	-0.0047, 0.0012
Parks	0.0001	-0.0022, 0.0025	-0.0009	-0.0048, 0.0030	-0.0004	-0.0049, 0.0041
Off-premise alcohol outlets	0.0001	-0.0023, 0.0025	0.0001	-0.0042, 0.0040	-0.0012	-0.0052, 0.0028
Police stations	-0.0006	-0.0025, 0.0013	0.0002	0.00031, 0.0035	-0.0009	-0.0041, 0.0023
Churches	0.0009	-0.0020, 0.0039	0.0044	-0.0009, 0.0097	0.0006	-0.0056, 0.0069
Libraries	-0.0001	-0.0019, 0.0016	-0.0007	-0.0038, 0.0024	-0.0008	-0.0037, 0.0021
Network quality	-0.0037**	-0.0056, -0.0019	-0.0073**	-0.0113, 0.0034	-0.0050*	-0.0092, -0.0009

* p < 0.05

** p < 0.0005

Model 1 covariates: Income, number of network members

Model 2 covariates: Number of network members

Model 3 covariates: Age, education, number of network members

Table 4

Predictors of risky spaces

	Model 1: Risky spaces (marijuana or alcohol)			Model 2: Risky marijuana spaces			Model 3: Risky alcohol spaces			Model 4: High risk spaces (marijuana and alcohol)		
	B	95% CI		B	95% CI		B	95% CI		B	95% CI	
% Unemployed	0.2174	-0.0286, 0.4633		0.1023	-0.1271, 0.3317		0.0535	-0.3558, 0.4629		0.2766	-0.4582, 1.0114	
% Owner-occupied housing	0.0217	-0.5476, 0.5909		0.2760	-0.2663, 0.8183		-0.2575	-1.1691, 0.6540		0.4978	-0.7794, 1.7750	
Median household income	-0.0948	-0.5860, 0.3963		-0.3752	-0.8388, 0.0883		-0.1878	-1.1336, 0.7579		-1.1514	-2.7153, 0.4125	
Crime index	-0.1068	-0.3729, 0.1597		-0.0743	-0.3402, 0.1916		-0.0783	-0.4146, 0.2580		-0.0504	-0.6640, 0.5632	
Parks	0.0644	-0.2179, 0.3467		0.0829	-0.1710, 0.3368		-0.6420	-1.4404, 0.1564		-1.1380**	-2.1499, -0.2166	
Off-premise alcohol outlets	-0.0694	-0.4490, 0.3102		-0.0711	-0.4322, 0.2899		0.5990	-0.1675, 1.3655		1.2556***	0.5847, 1.9266	
Police stations	-0.1217	-0.3960, 0.1525		-0.0933	-0.3489, 0.1624		-0.1969	-0.6428, 0.2490		-0.9780**	-1.7393, -0.2166	
Churches	0.0219	-0.1322, 0.5360		0.2702	-0.0639, 0.6042		-0.3980	-0.9293, 0.1332		-0.3320	-1.2612, 0.5973	
Libraries	-0.3904**	-0.7278, -0.0530		-0.2804	-0.6222, 0.0614		-0.2507	-0.8705, 0.3691		0.0748	-1.0724, 1.2237	
Network quality	-1.1786***	-1.5184, -0.8388		1.1076***	-1.4351, -0.7800		-0.5126**	-0.9293, -0.0960		-0.5089***	-0.8965, 0.1213	

*
p < 0.10**
p < 0.05***
p < 0.005

Model 1 covariates: Race, number of network members

Model 2 covariates: Race, number of network members

Model 3 covariates: Number of network members

Model 4 covariates: Number of network members