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Evaluating Substance Use In A Network Of Emerging Adult Males Via Analysis Of Text Messages Sent And Received

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EVALUATING SUBSTANCE USE IN A NETWORK OF EMERGING ADULT MALES VIA ANALYSIS OF TEXT MESSAGES SENT AND RECEIVED

By

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Abstract

Introduction: With the ubiquity of mobile phones, mobile health (mHealth) has the ability to transform healthcare specifically in regard to substance use interventions. Current mHealth interventions targeting substance use are limited as they require self-monitoring and user input.

Objectives: The objective of this study was to determine if text message content can predict substance use attitudes and behaviors. The aims were three-fold: (1) To assess the prevalence of discussion of substance use in text messages (2) To evaluate the relationship between text message content and substance use attitudes and behaviors; and (3) To examine social network structure using texting interactions related to substance use.

Methods: Text messages from 91 males ages 18-25 were monitored over a period of six months and examined for content related to substance use. Self-report data indicating substance use attitudes and behaviors were used to determine relationships between text message content, social network structure, and substance use attitudes and behaviors.

Results: In total, 23,173 text messages were analyzed with 166 text messages including alcohol related terms and 195 text messages including drug related terms. Individuals who sent text messages related to alcohol use were more likely to have problematic alcohol use and positive attitudes toward alcohol use, and individuals who sent text messages related to marijuana use reported higher frequency of marijuana use and more positive attitudes toward marijuana use. Individuals with problem alcohol use were in positions that controlled the network structure whereas individuals with problem marijuana use were in positions that had less control over network structure.

Conclusion: The results of this study indicate that monitoring text message content and social network structure among emerging adult males can potentially predict substance use attitudes and behaviors. This may allow for development of real-time interventions aimed at predicting and reducing problematic substance use.

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Introduction

Emerging adulthood (age 18-25) is an important period of developmental transition for men between adolescence and adulthood where men seek employment or education, and relationships (1, 2). During this time, peers become more influential as men increasingly become independent from their family as they seek to establish their own identities (3, 4). Additionally, it is a period when behavioral patterns related to alcohol and drug use can peak (2, 5, 6), and heavy use of alcohol and drugs at this phase are predictors for alcohol and substance use disorders later in life (7-10).

Social network theory is based on the idea that individuals are affected by directly and indirectly interacting with their own friends as well as with friends of friends (11). Use of alcohol and other substances have been linked to an individual's social network (12) with peer substance use being a strong predictor of individual substance use (13). The association between individual substance use and involvement in social networks with high levels of substance use may be due to socialization in which peers model substance use behavior, provide opportunities for substance use, and encourage attitudes and expectations that are positive toward substances (14, 15). The composition and quality of social networks during emerging adulthood may be of particular influence as men spend less time with families and more time with peers (3).

Mobile phones are used by approximately 94% of adults (16), and as a result, mobile health (mHealth), the application of mobile and wireless technology to support health objectives, is a rapidly growing field in preventative medicine. With existing mobile technology infrastructure and the high prevalence of mobile phone use, mHealth has the ability to transform health service delivery. In particular, mobile phones can monitor various behaviors of users and deliver interventions in real-time in the individual's natural environment (17-20). It is widely known that continuing care is most effective for addiction treatment, but this becomes more difficult once patients have completed treatment and leave the clinic (21, 22). mHealth provides the opportunity to increase self-management and make continuing care widely available to those not receiving inpatient care (20).

Current mHealth applications that target alcohol and substance use disorders include text message monitoring and reminder systems to monitor alcohol use or remind the individual to report alcohol consumption, intervention systems that monitor alcohol use but also deliver text messages to promote abstinence and recovery, and comprehensive recovery management systems that have internal sensors (like GPS) to deliver multifaceted messages and interventions (18, 23-25). Although many applications for treatment of substance use disorders exist, none have shown substantial effectiveness, and all are insufficient as interventions for treating substance use disorders (20). These applications require users to self-monitor alcohol and drug use, but technology with the capability to predict alcohol and other substance use without requiring user inputs may be more a more efficient way to prevent alcohol and drug use.

Advances in social technologies offer new tools and opportunities for large-scale data collection and analysis of social networks previously not available. As a result, there is a substantial basis of literature assessing the role that social technologies can play at understanding social networks and predicting user health and behavior with topics of focus including risky sexual behavior, substance use, mental health issues, and medical conditions (26-29). For example, a number of studies have examined how exposure to alcohol or drug related content on social networking sites such as Facebook, Twitter, Instagram, and Snapchat is associated with substance use behaviors and attitudes (30-35). Although there is a breadth of research examining a number of social technologies, the role that text messaging content sent through mobile phones may play in understanding health behavior has been neglected from the literature thus far. With the ubiquity of cell phone use, analyzing text message content may be a novel approach to understand health and behavior among networks of friends for the purposes of designing real-time interventions aimed at preventing problem substance use behaviors.

The goal of this research is to examine the relationship between text message content related to substance use and substance use behavior and attitudes among a network of emerging adult males. The primary aims are to:

1) Assess the prevalence of discussion of substances and alcohol use in text messages
2) Examine the relationship between sending and receiving text messages related to substance use on problematic substance use, frequency of substance use, and substance use attitudes.
3) Evaluate social network structure using texting interactions related to substance use.

To our knowledge, this is the first study that seeks to understand how text message content can be linked to social network structure and peer influence of health and behavior. Results from this study will demonstrate the effectiveness of using text message content and social network structure to predict risky behavior relating to alcohol and substance use. Findings will better enable researchers to develop new and effective mHealth technologies aimed at targeting alcohol and substance use.

Methods

Procedures

The study included 119 emerging adult men participating in a longitudinal study of social networks. Trained outreach workers recruited participants from areas of high risk (i.e. high crime, poverty) visiting locations frequented by emerging adult men. Snowball sampling was then used to recruit friends of participants, and participants were enrolled as they were identified by network members. Inclusion criteria included: 1) male gender; 2) age 18-25; 3) English-speaking; 4) heterosexual; 5) in possession of a cell phone with texting capabilities; and 6) ability to maintain cell phone service.

Participants were screened for eligibility in person or over the phone and scheduled for a baseline interview. Baseline assessments occurred between March 2011 and September 2013.

All participants provided written informed consent. Participants then completed an Audio Computer-Assisted Self Interview (ACASI) that collected self-reported information on demographics and substance use behaviors and attitudes. Additionally, participants consented to retrieval of all text messages sent and received over the course of six months from their cell phones. Due to snowball sampling methods, individuals were differentially followed over time in that text messages were retrieved from all individuals for a six-month period, however, if one individual engaged in texting interactions with another participant who had been followed over a different six-month period, there are a greater number of texts for that individual. Participants were compensated $75 for completing the computerized interview. All procedures were approved by the Yale University Human Investigation Committee.

Measures

Text mining was used to extract information related to substance use from all text messages sent and received by participants included in the study. The tm package in R (36) was used to determine the number of text messages sent and received by participants that related to substance use. A keyword list was developed that included common terms associated with alcohol use (i.e. liquor, alcohol, drunk) and drug use (i.e. weed, ounce, blunt), and this list was augmented after manually reading a subset of texts. Each text message sent and received by participants included in the study was processed to locate mentions of any keywords. Additional keywords related to substance use were identified by examining words frequently associated with each keyword.

The outcome measures included frequency of alcohol consumption, frequency of marijuana use, problematic alcohol consumption, problematic marijuana use, attitudes toward alcohol use, and attitudes toward marijuana use. Outcome measures were determined using information provided at baseline. Frequency of alcohol consumption was measured as the number of days a participant had at least one drink of alcohol during the previous 30 days. Frequency of marijuana consumption was measured as the number of days a participant used marijuana during the previous 30 days. Problematic alcohol use was a dichotomous variable assessed using the 3-item version of the Alcohol Use Disorders Identification Test (AUDIT) with standard cut-offs to define hazardous alcohol use (≥4). Prior studies have indicated that the 3-item AUDIT is comparable to the longer 10-item version for detecting problem alcohol use (37). Problematic marijuana use was a dichotomous variable defined by whether or not the participant indicated using marijuana 2 or more times per day.

Attitudes toward alcohol use and marijuana use were assessed using four items with 7 point Likert scales. Items began with "Drinking alcohol is:" or "Smoking marijuana is:" with the endpoints of Unpleasant/Pleasant, Fun/Boring, Bad/Good, and Wise/Foolish (38). Internal reliability for indicators was good for both alcohol (α=0.73) and marijuana indicators (α=0.91). A mean score for attitudes were calculated for alcohol use and marijuana use.

Several variables were used for statistical controls. Age was a continuous variable. Education level was coded as a categorical variable with three levels: some high school, high school degree attainment, and college degree attainment. Race was coded as a categorical variable with three levels: non-Hispanic African-American, Hispanic, and non-Hispanic White/other.

Analyses

Generalized Estimating Equations (GEE) were generated using SAS 9.4 (SAS Institute Inc, Cary, NC, USA) to assess whether frequency of texts sent or received related to substance use were associated with the primary outcomes. The participants (n=91) were the unit of analysis and were nested by recruitment network to control for correlation between individuals from the same network. The responses were assumed to be equally correlated, and therefore an exchangeable correlation structure was used as this is the structure recommended for this type of data. Age, race, and education were controlled for in the models. Additionally, due to differential follow-up times, total texts messages sent and received by individuals were used as a statistical control. As total texts messages sent and total texts messages received were collinear, the mean of total texts sent and received was used.

A social network of texting interactions was built for individuals in the network where individuals represented the vertices (nodes) and texting interactions represented the edges (links). A link existed between two individuals when they were both involved in a texting interaction. The networks were directed so that links were outgoing from the individual that sent a text and incoming for the individual that received the text. Unweighted directed networks showed whether or not there were any texting interactions between individuals. Weighted directed network links were weighted based on the frequency of texts related to alcohol or marijuana use. Statistical analysis and network visualization were conducted using the igraph package in R (39).

Measures of centrality were also calculated for each individual in the network. Both weighted and unweighted measures of centrality were calculated. The degree centrality measure shows how well-connected individuals are in the network (40, 41). It is a highly effective measure of influence as individuals with more connections tend to have more power (42). Taking into consideration the direction of links (i.e. whether an individual sent a text or received a text), it is necessary to distinguish between out-degree centrality and in-degree centrality. In an unweighted relationship, the occurrence of an interaction between any pair of individuals determines the presence of a link. Therefore, individuals with relatively high unweighted degree centrality, have more direct contacts, but it does not necessarily mean they sent or received more texts. Individuals with high unweighted out-degree centrality have more direct distinct contacts to which they sent texts, and individuals with high unweighted in-degree centrality have more direct distinct contacts from whom they received texts. In weighted relationships, the frequency of texts containing substance use content between two specific individuals is considered and defines the strength of the link or in other words the magnitude of the degree centrality. Therefore, weighted out-degree centrality is defined by the frequency of texts an individual sent containing terms related to alcohol or drug use, and the weighted in-degree centrality is defined by the frequency of texts an individual received containing terms related to alcohol or drug use.

The betweenness centrality measures the number of times an individual lies on the shortest path between other individuals in a group (43, 44). In other words, it is a measurement of the extent to which an individual indirectly links pairs of other individuals that are not directly linked as contacts. A geodesic is the shortest path connecting two individuals, and betweenness centrality for a particular individual is calculated by determining the number of geodisics between all pairs of other individuals that include the particular individual of choice (41). Conceptually, an individual that has a high betweenness centrality lies on many geodesics and is considered the bridge between individuals from different parts of the network that are not directly connected to one another (41). In social network analysis, individuals with high betweenness centrality are thought to control the social interactions within the group especially if they are the bridge between two network components (40, 41, 43). Removing these individuals will disrupt the network and can fragment it into groups as these individuals act as almost a gate-keeper between others in the network (43). Both unweighted and weighted measures of betweenness centrality were measured.

Measures of centrality were stratified by problem alcohol use, problem marijuana use, or any problem substance use. Spearman rank correlations were performed using SAS 9.4 to determine relationships between the centrality parameters and self-reported problem substance use.

Results

The sample consisted of 91 emerging adult males (Table 1). The mean age of participants was 20.63 years old, and participants were predominately non-Hispanic black (64.8%) or Hispanic (25.3%). Of all participants, 80 (87.9%) had at least a high school degree or GED, and 42 (46.2%) were not working. Any alcohol use in the previous year was reported by 73 (79.1%) individuals and previous life-time marijuana use was reported by 70 (76.92%) individuals. Twenty-nine (31.9%) of individuals had problem alcohol use and 35 (38.5%) of individuals had problem marijuana use.

In total, there were 23,173 text messages sent and received between the 91 participants included in the study. There were 166 text messages that included alcohol related terms and 195 text messages that included drug related terms. Figure 1 visually displays the frequency of words related to substance use. Although the overall number of text messages depicting substance use was low, 30 (33.0%) participants sent text messages related to alcohol, 31 (34.1%) participants received text messages related to alcohol, 38 (41.8%) participants sent texts related to drug use, and 36 (39.6%) participants received texts related to drug use. In total, 44 (48.4%) individuals sent at least one message containing any mentions of alcohol or drug use, and 47 (51.6%) individuals received at least one message containing any mention of alcohol or drug use.

GEE analyses were performed to explore correlates of substance use attitude and behaviors. Predictors modeling alcohol use attitudes and behaviors included number of texts sent containing alcohol related terms and number of texts received containing alcohol related terms. Predictors modeling marijuana use attitudes and behaviors included number of texts sent containing marijuana related terms and number of texts received containing marijuana related terms.

Individuals who sent more texts containing terms related to alcohol were more likely to have positive attitudes toward alcohol use ($\beta=0.0823$, $p<0.01$) (Table 2). Additionally, those with increased number of texts sent containing alcohol related terms were 1.11 times (95% CI: 1.04-1.18) more likely to have problematic alcohol use (Table 3). Interestingly, receiving more texts containing alcohol related terms was negatively associated with attitudes toward alcohol use, problem alcohol use, and days of alcohol use (Table 2, Table 3).

Individuals who sent more texts with marijuana related content were more likely to have positive attitudes toward marijuana use (β=0.0823, $p<0.01$) (Table 2). Additionally, for 30-day marijuana use, sending texts with marijuana related content was significantly associated with frequency of marijuana use in the previous 30 days (β=0.77, $p<0.01$) (Table 2). For problematic marijuana use, sending or receiving text messages with marijuana related content was non-significant (Table 3).

Figure 2 shows the unweighted non-directed social network of all texting interactions where individuals are represented by nodes color-coded by problem substance use and texting interactions are depicted by edges (number of connections with distinct individuals). There were 176 linkages total with an average number of 3.96 linkages per person. The mean degree (number of contacts per person) was 3.50 for those without problem substance use, 4.65 for those with only problem alcohol use, 3.75 for those with only problem marijuana use, and 3.52 for those with both problem alcohol and marijuana use. The mean unweighted betweenness score was 24.11 for those without problem substance use, 51.93 for those with problem alcohol use, 14.29 for those with problem marijuana use, and 14.17 for those with both problematic alcohol and substance use (Table 4).

Figure 3 shows the directed social network of texting interactions weighted by number of texts containing alcohol related terms, stratified by problematic alcohol use. Those with problematic alcohol use had a mean out-degree centrality of 4.31 and those without problematic alcohol use had a mean out-degree centrality of 2.95. Those with problem alcohol use had a mean betweenness score of 34.48 and those without problem alcohol use had a mean betweenness score of 25.94 (Table 5).

Figure 4 shows the directed social network of texting interactions weighted by number of texts containing content related to marijuana use. Those with problem marijuana use had a mean out-degree centrality of 7.00 and a betweenness score of 15.53. Those without problem marijuana use had a mean out-degree centrality of 4.93 and a mean betweenness score of

42.16. The mean betweenness score for those without problem marijuana use was significantly different from the mean betweenness score for those with problem marijuana use (p=0.048).

Discussion

This study utilized text conversations between emerging adult males to examine the relationship between sending and receiving texts and social network structure on substance use attitudes and behaviors. Results indicate that substance use is high among this population. Of the individuals that participated, 79.1% reporting alcohol use in the previous year and 31.9% of individuals had problem alcohol use. Rates of lifetime marijuana use were also high with 76.9% reporting marijuana use and 38.5% of individuals having problem marijuana use. Additionally, although overall rates of texting about substance use were low, 33.0% of individuals sent texts messages with alcohol related content, 41.8% of individuals sent text messages with drug related content, and 48.4% of individuals sent text messages with any substance use related content.

Results from this study indicate that sending texts messages containing alcohol or marijuana related content is indicative of substance use attitudes and behaviors for both marijuana and alcohol use. Participants sending alcohol related texts were more likely to have problematic alcohol use and more positive attitudes toward alcohol use. Individuals that sent texts with marijuana related content were more likely to have smoked on more days in the previous month and more positive attitudes toward marijuana use. Receiving texts related to marijuana use was not a predictor for marijuana use attitudes and behaviors suggesting that individuals may not be being influenced by their peers. Moreover, those who received increased texts related to alcohol use were less likely to have positive attitudes toward alcohol use and problematic alcohol use behaviors. This suggests that among this social network, substance use attitudes and behaviors are not being encouraged by receiving text messages containing substance use related terms from peers.

With respect to network attributes, individuals had similar mean degrees of unweighted connectivity regardless of their status of problematic substance use. Betweenness centrality was also measured as this allowed for identification of individuals who served as bridges between individuals in the network and therefore potentially could control the network structure (41). It was included as it can be interpreted as an indirect measure of influence as individuals with high betweenness have control over the spread of information across the network (43). Although not significant, individuals with only problematic alcohol use did have relatively high unweighted betweenness scores as compared to individuals without problematic alcohol use indicating that these individuals may be important for controlling the social connections between the group. This finding was also supported by the weighted measures of centrality where individuals with problem alcohol use had relatively higher weighted betweenness scores than those without. This relationship is consistent with previous analyses assessing social network structure and substance use among peers, which found higher levels of betweenness centrality predicted alcohol use (45-47).   Taken together with these other studies, these results suggest that individuals with problematic alcohol use may have more control of the social network and a greater potential to encourage problematic alcohol consumption in more peers.

Individuals with only problematic marijuana use and both problematic marijuana and alcohol use have relatively lower unweighted betweenness scores suggesting that these individuals have less control over the social connections between the group. More specifically, those with problematic marijuana use had significantly lower weighted betweenness scores suggesting they were more isolated than those without problematic marijuana use. This finding is important as those with problematic marijuana use have less connectivity to encourage and influence problematic marijuana use among peers. Previous studies that sought to understand the relationship between marijuana use among peers have suggested that more popular individuals are more likely to to have previous marijuana use (6, 48-50), which conflicts with our findings. One potential explanation for the conflicting results is that previous studies have assessed any marijuana use in a given time period whereas the outcome measured here is problem marijuana use. We defined problem marijuana use as using marijuana more than one time in a given day in the previous 30 days. It could be that casual marijuana users may be centrally located and popular and problem marijuana users may be more isolated. We feel it is important to measure problem marijuana use rather than any use as problem users are the individuals most at risk for marijuana use associated harms. More frequent use of marijuana is associated with poor academic achievement, family problems, increased likelihood of using other drugs, and postponement of marriage and employment (51-56). Additionally, heavy use has been associated with cognitive impairments and higher levels of anxiety, depression, and suicidal ideation (57-63). As such, additional studies should be conducted among larger networks to better understand the relationship between network structure and problematic marijuana use rather than just any marijuana use as this study suggests that these individuals may be harder to reach in terms of network structure which would impact intervention strategies.

These results have a number of important public health implications and add to the increasing literature emphasizing the utility of using social technologies to predict substance use behaviors. Although a number of mHealth interventions targeting alcohol and substance use have been implemented, they all require user inputs and self-monitoring which can limit their effectiveness (64-67), and interventions that can predict risky behavior to design real-time targeted interventions are urgently needed. Social technologies including Twitter, Instagram, Snapchat, and Facebook provide a massive resource of data that have been used to better understand substance use health and behaviors (68-72). These social technologies allow for the possibility for design of interventions aimed at reducing risky behaviors that target the most influential individuals in a network. The results of this study add to the growing body of literature and demonstrate a novel way in which social technologies can be linked to health and behavior through social network and content analysis of the data provided by text messaging interactions.

There are several limitations to this study. One limitation is that individuals were differentially followed over time due to the snowball recruitment strategy. For example, text messages were retrieved from all individuals for a six-month period, however, if one individual engaged in texting interactions with another participant who had been followed over the course of a different six-month period, there are a greater number of texts for that individual. We controlled for this possibility of differential follow-up by including the mean number of texts sent and received by each individual in our model. Another limitation was that the small sample size limited the statistical power of this analysis particularly for the assessment of differences in centrality parameters and prevented the addition of covariates into the model. Additionally, substance use behaviors were all indicated through self-report and individuals knew in advance that their text messages were being monitored which could have limited open discussions surrounding substance use. Participants all received Certificates of Confidentiality to discourage this potential bias. Finally, this study focused on a population of male high risk individuals, ages 18-25, and the results of this study may not be generalizable to the general population.

Despite these limitations, this study demonstrates a novel approach to examining substance use behavior and social networks. To our knowledge, this is the first study examining the potential of peer influence through text messages and social network structure based on text messages sent and received. As cell phone use is ubiquitous and text messaging is a primary means of communication for many individuals, predicting substance use behavior by monitoring text messages could encourage the development of real-time mHealth interventions to prevent risky substance use behaviors.

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Tables

Table 1: Participant Demographics and Characteristics [a]

	N=91 [b]
Demographics	
Age	20.63 (1.8)
Race	
Non-Hispanic White	3 (3.3)
Hispanic	23 (25.3)
Non-Hispanic Black	59 (64.8)
Other	6 (6.6)
Education	
Less than high school	11 (12.1)
High school degree or GED	33 (36.3)
Some College	39 (42.9)
College degree	5 (5.5)
Graduate degree	3 (3.3)
Annual Household Income	
$ 0-4,999	22 (24.2)
$5,000-9,999	11 (12.1)
$10,000-14,999	11 (12.1)
$15,000-24,999	10 (11.0)
$25,000-34,999	7 (7.7)
$35,000-49,999	9 (9.9)
$50,000 or more	11 (12.1)
Employment	
Not working	42 (46.2)
Part-time employment	32 (35.2)
Full-time employment	17 (18.7)
Relationship Status	
Single	37 (40.7)
In a relationship	54 (60.3)
Children	
No children	71 (78.0)
1 or more children	20 (22.0)
Living Situation (not mutually exclusive)	
Live with mother/father	51 (56.0)
Live with biological children	3 (3.3)
Live with partner	7 (7.7)
Live with sibling	25 (27.5)
Live with other relative	21 (23.1)
Live with friend	6 (6.6)
Live alone	6 (6.6)
Outcomes	
Alcohol Use	72 (79.1)
Marijuana Use	70 (76.9)
Problem Alcohol Use	29 (31.9)
Problem Marijuana Use	35 (38.5)

[a] Table values are mean ± SD for continuous variables and n (column %) for categorical variables.
[b] Percentages may not sum to 100% due to rounding or missing variables.

Table 2: Multivariate GEE analysis associations between text messages sent and received containing substance use related terms and substance use attitudes and behaviors

	Marijuana Attitudes		**Alcohol Attitudes**		**Days of Marijuana Use**	
	β	p	β	p	β	p
Age	0.0260	0.70	0.1649	<0.01	0.2417	0.74
Race/Ethnicity						
Non-Hispanic White/Other	Reference	--	Reference	--	Reference	--
Hispanic	0.5006	0.32	0.1841	0.64	2.49	0.57
Non-Hispanic Black	0.3016	0.36	0.0901	0.82	1.27	0.69
Education						
Some High School	Reference	--	Reference	--	Reference	--
Completed High School	-1.1553	0.04	-0.2112	0.53	-6.98	0.21
Completed College	-0.9682	0.18	-0.0930	0.80	-8.30	0.22
Sent Alcohol Related Texts	--	--	0.0160	0.04	--	--
Received Alcohol Related Texts	--	--	-0.0126	<0.01	--	--
Sent Marijuana Related Texts	0.0823	<0.01	--	--	0.77	<0.01
Received Marijuana Related Texts	-0.0229	0.28	--	--	0.32	0.13
Mean of Total Texts Sent & Received	-0.0005	0.04	0.0003	0.06	-0.01	<0.01

Table 3: Multivariate GEE analysis examining associations between text messages sent and received containing substance use related terms and problematic substance use and behaviors

	Problematic Alcohol Use	**Problematic Marijuana Use**	**Days of Alcohol Use**
Age	1.46 (0.95-2.25)	0.89 (0.74-1.07)	1.49 (1.04-2.13)
Race/Ethnicity			
Non-Hispanic White/Other	Reference	Reference	Reference
Hispanic	2.18 (0.38-12.63)	0.46 (0.06-3.28)	3.78 (0.68-20.80)
Non-Hispanic Black	1.74 (0.48-6.39)	0.64 (0.21-2.01)	2.14 (0.43-10.69)
Education			
Some High School	Reference	Reference	Reference
Completed High School	0.46 (0.11-1.84)	0.68 (0.07-6.68)	0.67 (0.15-2.92)
Completed College	0.31 (0.05-2.11)	0.33 (0.03-4.20)	1.14 (0.18-7.36)
Sent Alcohol Related Texts	1.11 (1.04-1.18)	--	1.00 (0.98-1.04)
Received Alcohol Related Texts	0.94 (0.92-0.97)	--	0.97 (0.94-0.99)
Sent Marijuana Related Texts	--	1.16 (0.88-1.51)	--
Received Marijuana Related Texts	--	1.04 (0.88-1.23)	--
Mean of Total Texts Sent & Received	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)

Table 4: Mean of unweighted centrality parameters, stratified by problematic substance use

	Problematic Substance Use				
	None	Only Alcohol	Only Marijuana	Alcohol & Marijuana	p
Degree	3.50	4.65	3.75	3.52	0.306
Out-Degree	1.67	2.31	2.00	1.83	0.837
In-Degree	1.83	2.35	1.75	1.70	0.815
Betweenness	24.11	51.93	14.29	14.17	0.544

Table 5: Mean of centrality parameters both unweighted and weighted by frequency of texts sent and received relating to substance use

	Problem Alcohol Use			**Problem Marijuana Use**		
	Yes	No	p	Yes	No	p
Unweighted						
Degree	4.12	3.57	0.338	3.60	4.04	0.461
Out-Degree	2.08	1.81	0.461	1.71	2.07	0.266
In-Degree	2.04	1.76	0.300	1.88	1.96	0.804
Betweenness	34.21	21.31	0.308	14.21	37.03	0.077
Weighted						
Degree	7.92[a]	6.71[a]	0.680	13.97[b]	9.88[b]	0.136
Out-Degree[c]	4.31[a]	2.95[a]	0.925	7.00[b]	4.93[b]	0.209
In-Degree[d]	3.62[a]	3.76[a]	0.399	6.97[b]	4.95[b]	0.175
Betweeness	34.48[a]	25.94[a]	0.508	15.53[b]	42.16[b]	0.048

[a] Weighted by texts related to alcohol use
[b] Weighted by texts related to drug use
[c] Weighted by texts sent
[d] Weighted by texts received

Figures

Figure 1: Word cloud depicting frequently used words relating to substance use. Each word's frequency is correlated with font size.

Figure 2: Social network of texting interactions where individuals are represented by nodes color coded by problematic substance use and texting interactions are depicted by edges

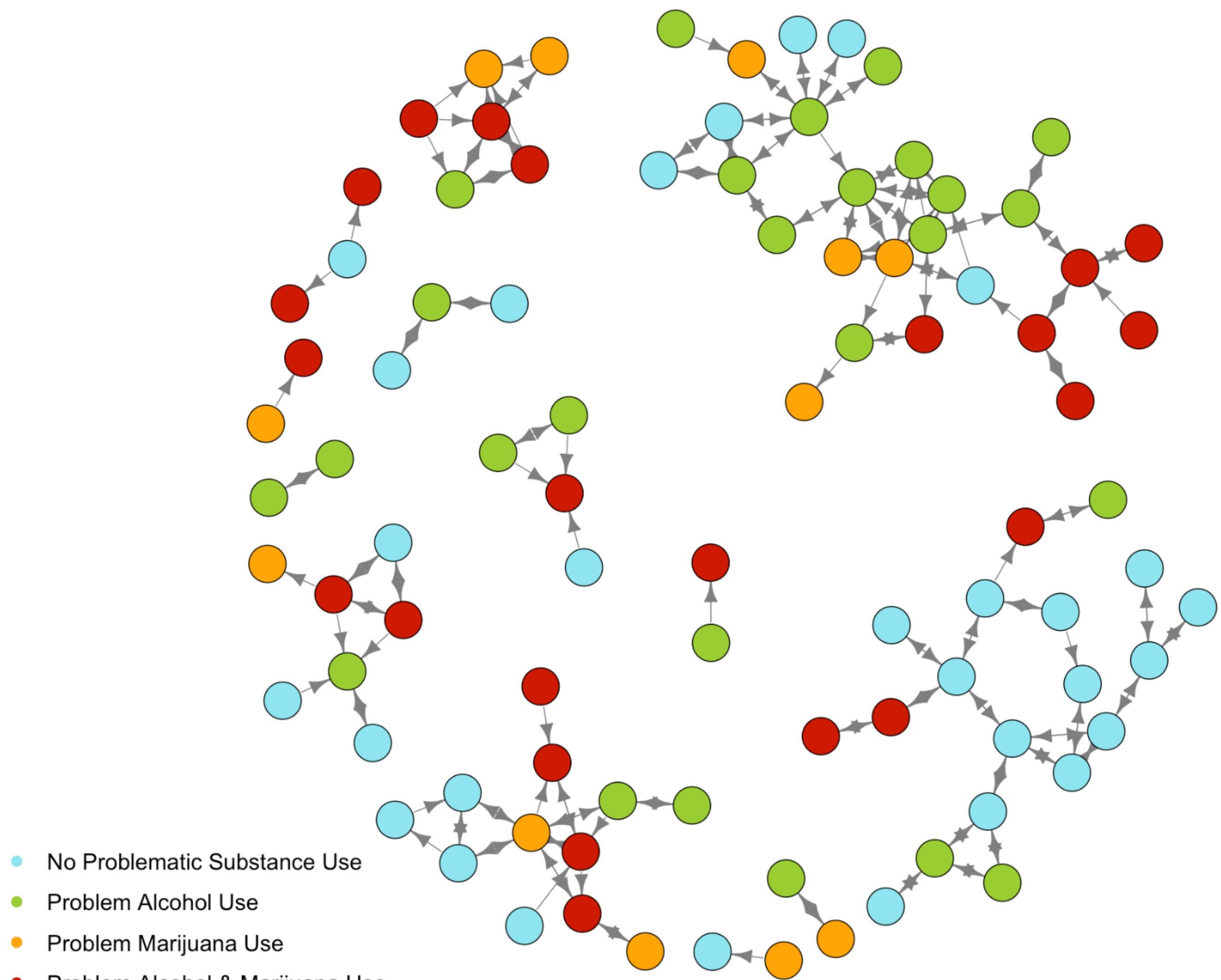

Figure 3: Social network of texting interactions where individuals are represented by nodes color coded by problematic alcohol use and texting interactions are depicted by edges weighted by frequency of texts involving alcohol related terms

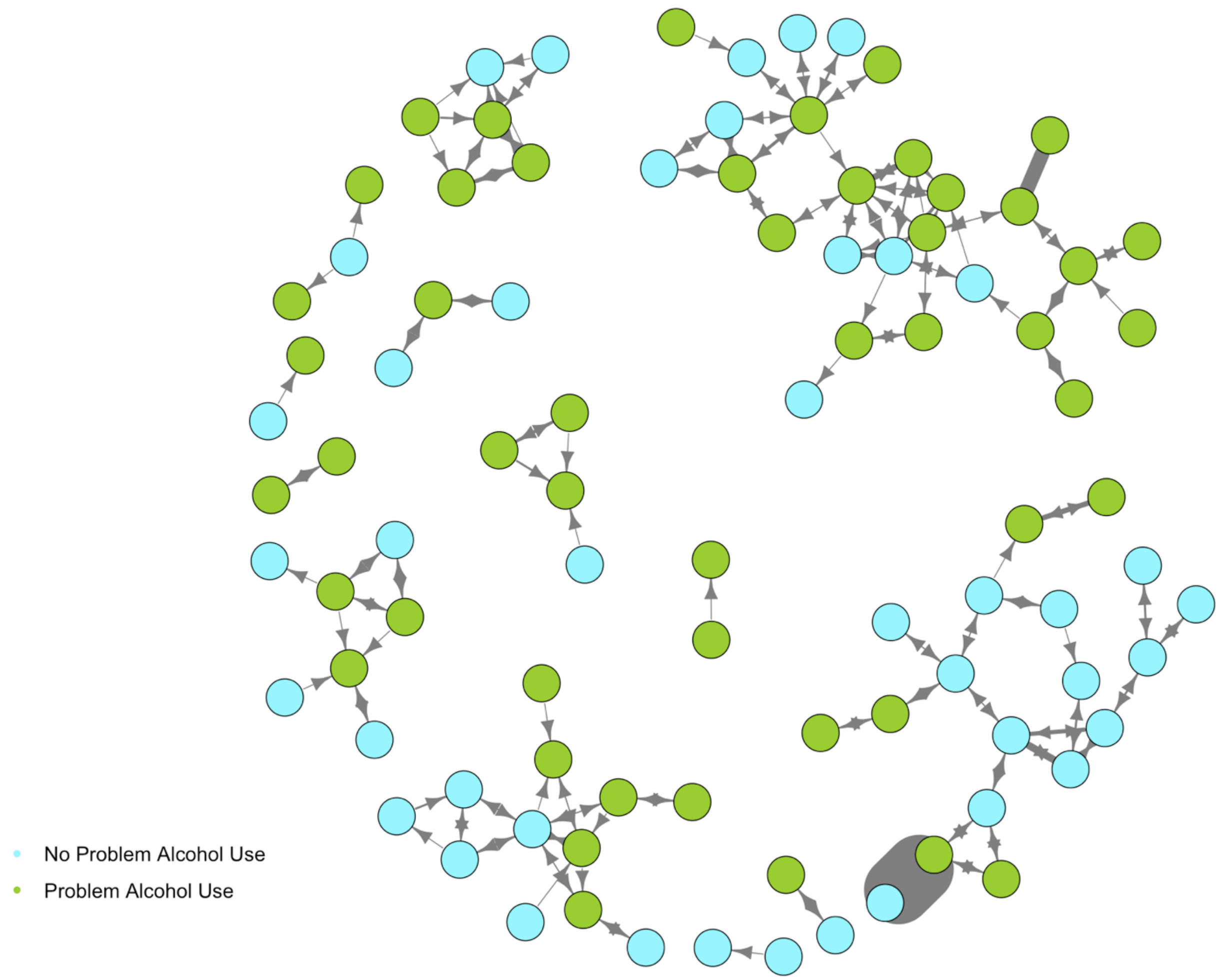

Figure 4: Social network of texting interactions where individuals are represented by nodes color coded by problematic marijuana use and texting interactions are depicted by edges weighted by frequency of texts involving marijuana related terms