HHS Public Access
Author manuscript
J Subst Abuse Treat. Author manuscript; available in PMC 2022 December 01.

Published in final edited form as:
J Subst Abuse Treat. 2021 December ; 131: 108392. doi:10.1016/j.jsat.2021.108392.

Longitudinal Effects of Social Network Changes on Drinking Outcomes for Individuals with a First-Time DUI

Mauri Matsuda, Ph.D.[a], **Karen Chan Osilla, Ph.D.**[b], **David P. Kennedy, Ph.D.**[b], **Susan M. Paddock, Ph.D.**[c]

[a]Portland State University, 550 Urban Center, 506 SW Mill Street, Portland, OR 97203

[b]RAND Corporation, 1776 Main Street, PO Box 2138, Santa Monica, CA 90407

[c]NORC at the University of Chicago

Abstract

Background.—Social networks are important predictors of alcohol-related outcomes, especially among those with a DUI where riskier social networks are associated with increased risk of drinking and driving. Social networks are increasingly a target for intervention; however, no studies have examined and measured whether longitudinal changes in social networks are associated with reductions in impaired driving.

Objective.—The current study first examines longitudinal changes in social networks among participants receiving services following a first-time DUI, and then examines the association between network change and drinking outcomes at 4- and 10-month follow-up.

Methods.—The study surveyed a subsample of participants (N=94) enrolled in a clinical trial of individuals randomized to cognitive behavioral therapy (CBT) or usual care (UC) on an iPad using EgoWeb 2.0—an egocentric social network data collection software—about pre-DUI and post-DUI networks and their short- and long-term drinking behaviors.

Results.—Participants were 65% male, 48% Hispanic, and an average of 32.5 years old. Overall, participants significantly reduced the proportion of network members with whom they drank from .41 to .30 (p=0.001) and with whom they drank more alcohol than they wanted to from .15 to .07 (p=.0001) from two weeks prior to the DUI (measured at baseline) to 4-month follow-up. Furthermore, decreases in proportion of drinking partners over time were associated with reduced drinks per week, self-reported driving after drinking, and intentions to drive after drinking at 4-month follow-up. Participants who reported decreases in proportion of drinking partners also reported significantly less binge drinking at 10-month follow-up. Finally, increases in emotional

Correspondence should be sent to Mauri Matsuda, Portland State University, 550 Urban Center, 506 SW Mill Street, Portland, OR, 97203. mmatsuda@pdx.edu. Phone: 503-725-6256. Fax: 503-725-5162.
Mauri Matsuda: Conceptualization, Formal analysis, Writing – Original Draft **Karen Osilla:** Conceptualization, Writing – Review & Editing **David Kennedy:** Methodology, Writing – Review & Editing **Susan Paddock:** Methodology, Writing – Review & Editing

support were associated with decreases in binge drinking at 4-month follow-up. The study found no differences in the changes in composition of networks between CBT and UC groups.

Conclusions.—These results suggest that individuals receiving services in DUI programs significantly reduced risky network members over time and that these social network changes were associated with reduced drinking and other indicators of risk for DUI recidivism. Clinical interventions that target reductions in risky network members may improve outcomes for those enrolled in a DUI program.

Keywords

Driving under the influence; Egocentric social network analysis; Cognitive behavioral therapy

1. Introduction

Driving under the influence of alcohol (DUI) is the number one cause of traffic-related fatalities and remains a persistent issue with considerable human, social, and economic costs (Blincoe et al., 2015). Drivers involved in alcohol-related fatalities are 4.5 times more likely to have a prior conviction for DUI than drivers involved in non-alcohol-related fatalities (USDOT, 2020). Thus, effectively preventing recidivism will have a significant impact on reducing fatalities and other harmful outcomes associated with DUI.

Extensive research shows that social networks can contribute to abstinence among those seeking treatment for alcohol dependence (Kelly et al., 2009). In a systematic review, Kelly and colleagues (2009) identified 19 studies examining the mechanisms of behavior change for Alcoholics Anonymous (AA) and other 12-step treatment programs, including four studies that examined social change mechanisms such as network size and support for abstinence, friendship quality, social support, and pro-drinking influences. These studies suggested that the beneficial effects of programs such as AA are at least partially mediated by changes in social networks. Research has shown that the proportion of heavy/problem drinkers and those encouraging alcohol reduction in one’s social networks were significantly associated with abstinence among individuals seeking treatment in alcohol treatment programs (Bond et al., 2003). Adults in residential treatment who participated in AA were more likely to reduce pro-drinking ties and increase pro-abstinence ties to their four most important people between treatment entry and 9-month follow-up, and these changes explained the effect of AA participation on 15-month follow-up abstinence and drinking intensity (Kelly et al., 2011). Furthermore, evidence from emerging adults in residential treatment programs indicates that high-risk friends decreased and low-risk friends increased throughout the recovery period, although this change did not mediate participation in 12-step programs such as AA (Kelly et al., 2014). Relatedly, a study found social support, particularly from AA-based network members, for reducing drinking and drug use to be associated with reduced drinking-related outcomes (Kaskutas et al., 2002).

Thus, ample evidence exists for the importance of social networks—particularly alcohol-specific aspects of networks, such as ties to individuals who encourage abstinence—in the treatment and recovery process. Recent research demonstrates that social networks are also important risk factors for drinking and related behaviors among individuals convicted of a first DUI (Matsuda et al., 2020). Specifically, research has found that having riskier networks in the two weeks prior to a DUI to be associated with greater frequency and likelihood of drinks per week, binge drinking, alcohol use, marijuana use, and alcohol-related consequences among individuals enrolled in three-month DUI programs (Matsuda et al., 2020). Although prior research has underscored the importance of social networks for changes in alcohol-related behaviors and dynamic processes of recovery, few studies have examined how social networks are associated with the risk for DUI, with prior work being cross-sectional and therefore unable to elucidate the effect of longitudinal changes in social networks. Further, no studies have specifically addressed whether and how networks change following a DUI and how these potential changes in the network may influence drinking outcomes.

Increasingly, researchers have begun to incorporate social network interventions into behavioral change programs (Shelton et al., 2018) such as cognitive behavioral therapy (CBT). Social network interventions (Kennedy et al., 2016; Kennedy et al., 2018a; Kennedy et al., 2018b), which use visualizations of individual's social networks to inform individuals about the role of social networks in influencing alcohol misuse, may enhance CBT and other interventions by more effectively highlighting the positive and negative influence of risky or supportive network members. Although several strategies are effective for preventing DUI, CBT represents one underutilized approach that may significantly reduce DUI recidivism given that having an alcohol use disorder (AUDs) is a risk factor for DUI recidivism (McCutcheon et al., 2011; Osilla et al., 2019) and research has demonstrated CBT to be effective at reducing alcohol use disorders (Monti et al., 2002). For example, one study found that individuals in a DUI program receiving CBT reported significantly lower odds of driving after drinking than those who received usual care (Osilla et al., 2019). CBT may furthermore affect networks by providing individuals with problem solving and coping skills that can assist in addressing social influences associated with alcohol use and related consequences. Despite the promise and growth in development of social network interventions, few studies have examined or measured how networks change over time and whether these changes contribute to behavior change.

1.1 Current study

Despite evidence that underscores the importance of social networks in influencing health outcomes and promoting alcohol use and alcohol abstinence, few studies have directly measured and analyzed the social networks of DUI populations (Beck et al., 2011), whether and how networks change following a DUI incident or in response to intervention, and whether network changes influence drinking outcomes. Understanding these outcomes is critical to understanding how to prevent future DUI. In the current study, we examine changes in the composition of egocentric social networks[1] among participants in first-time DUI programs who were randomly assigned to receive CBT or usual care (UC). The goals of the current study were to examine (1) changes in the composition of social networks after a DUI, (2) whether network changes were related to CBT assignment, and

[1]In this paper, we use the terms *social networks* and personal *networks* interchangeably to refer to sets of relationships among people who interact with one another.

(3) whether network changes were associated with differences in DUI-related outcomes—drinking frequency, binge drinking, self-reported driving after drinking, and intentions to drive after drinking at 4- and 10-month follow-up.

2. Material and methods

2.1 Settings, procedures, and participants

This study recruited participants from a larger randomized controlled trial (RCT) comparing the effects of CBT versus UC on individuals mandated for license reinstatement to three first-time DUI programs in Ventura County, California. Participation in this larger RCT was voluntary, and research staff recruited participants between July 2016 and June 2017 at DUI program intake if receiving English-language services and meeting eligibility criteria. All participants were over 21 years old; had at least a fifth-grade education; had a first DUI conviction within the past year; and scored over 3 on the AUDIT-C (Alcohol Use Disorders Identification Test), a 3-item screening tool to identify individuals with hazardous drinking or an active alcohol use disorder. Following randomization to CBT or UC, participants completed a three-month program that involved weekly 90-minute group sessions (CBT or UC), monthly individual counseling sessions, and biweekly 2-hour education classes required for license reinstatement. Participants completed self-report interviews in-person at baseline (prior to intervention), 4-month follow-up (upon completion of intervention), and 10-month follow-up.

For the current study, research staff approached participants in the larger RCT at baseline mid-way through the recruitment period (beginning in January of 2017) about completing an additional survey regarding their social networks. The study self-administered these surveys on an iPad using the egocentric social network survey software EgoWeb 2.0 (egoweb.info). The study re-interviewed participants who had been surveyed at baseline on an iPad at 4-month follow-up to assess changes in social networks; unfortunately, due to budget and time constraints the study did not complete similar social network interviews at 10-month follow-up. Of those approached at baseline (n=164), 73% consented to participate (n=120). Due to a technical error resulting in failure to upload data from 26 cases, data from these participants were lost and this resulted in a final analytic sample of 94 participants interviewed at baseline and 4-month follow-up distributed across intervention (n=51) and control (n=43) groups. Four participants were lost due to attrition at the 10-month follow-up. Upon investigation, we concluded that this glitch was random and did not systematically bias the representativeness of the sample. Participants who completed the social network survey received a $15 incentive payment at baseline and 4-month follow-up in addition to the $25 incentive for completing their baseline survey in the larger study. The RAND Human Subjects Protection Committee approved all procedures. Participants were 65% male, 48% Hispanic,[2] and 32.48 (range = 21–74, S.D. = 11.82) years old, with 67% reporting education greater than HS diploma/GED. Further details on sample characteristics, attrition, and procedures are available in previous publications (Osilla et al., 2019; Matsuda et al., 2020).

[2]The remainder of participants were nearly all white, non-Hispanic, with a small number reporting another race (n=6).

2.2 Social network measures

The study collected social network data by prompting participants ("egos") to name 10 individuals ("alters") in their social networks with whom they had interacted in the two weeks prior to their DUI at baseline, or in the past two weeks at the 4-month follow-up. The length of recall was greater (up to one year) for the baseline social network survey than the follow-up survey (two-weeks), a limitation that we note in our discussion. We asked one general name generator—a question used to elicit names of personal network members—to best identify those who would be most likely to interact with the ego during alcohol use and risk-taking behavior:

> Let's start off with naming 10 people you had contact with prior to your DUI. Think about the people who you interacted with the most (e.g. in-person, over the phone, by e-mail, via social media) in the [past two weeks/two weeks right before your DUI]. Please name only people who are at least 18 years old. Nicknames (e.g. mom, dad) are okay. Please list ten people, even if you had brief contact over [the past two weeks/two weeks prior to your DUI]. For example, think about people at home or work.

We used this broader measure of networks, rather than common measures used in alcohol studies such as the Important People Inventory (Zywiak et al., 2009), to assess the influence of both peripheral and core network members and therefore both weak and strong ties. Following standard procedures for collecting social network data and drawing on prior social network research (Crossley et al., 2015; Kennedy et al., 2010; McCarty et al., 2019; Perry et al., 2018), we asked several name interpreter questions—designed to elicit information about network member characteristics—to gather information about each alter/ network member regarding several characteristics such as relationship status, frequency of interaction, drinking behaviors, and level of support.

We assessed eight aspects of the participant's networks. We asked two questions related to how risky the network was: 1) whether participants drank with network members in the two weeks prior to their DUI and 2) whether participants drank more alcohol than they wanted to with network members in the two weeks prior to their DUI (yes=1, no=0). To assess drinking-specific and DUI-specific support, we asked participants four questions to assess 1) whether they thought their network members would be happy if they (the participant) reduced drinking, 2) whether they thought their network members would be happy if they (the participant) reduced drinking and driving, 3) whether network members provided them with support for reducing drinking, and 4) whether network members would have provided them with support for drinking at home instead of out (yes=1, no=0). Finally, to assess general dimensions of social support, we asked participants 1) whether their network members provided them with emotional support (e.g., encouragement and advice), and 2) whether their network members provided them with tangible support (e.g., car rides, money, or child care) (Hays et al., 1995) (yes=1, no=0).

At both waves, we calculated person-level measures of network composition by dividing the number of network members for whom the characteristic applied by the total number of network members; thus, these measures represented the proportion of each respondent's personal network sharing a given characteristic and can range from 0 to 1. We also created a second set of network measures to assess change in each of the social network measures we just described. We created these measures by subtracting network characteristics at baseline from network characteristics at 4-month follow-up. Due to complete or quasi-complete separation in preliminary logistic regression models, a problem that occurs when the variables in the model perfectly predict a response variable (Albert & Anderson, 1984; Allison, 2008), we collapsed these continuous measures into categorical measures coded with the following ranges: 1 = increase in proportion of network members, 0 = no change in proportion of network members, –1 = decrease in proportion of network members.

2.3 Outcome variables

The study assessed drinking outcomes using four separate dependent variables. The study assessed *binge drinking* by the frequency of consuming five or more drinks on one occasion monthly or more often (e.g. weekly, daily or almost daily). *Drinks per week* was a count measure representing the typical number of drinks consumed in a typical week in the past month. In addition, we examined two measures related to drinking and driving. The study assessed *intentions to drive after drinking* with a set of measures from the Behaviors & Attitudes Drinking & Driving Scale (BADDS), which has shown reliability and validity in previous studies (Jewell et al., 2008). We based our measure on a set of items that asked participants to report how likely they were to drive a short distance (a few blocks to a mile) after having one drink, two drinks, three to four drinks, five to six drinks, and over six drinks (very unlikely=0, somewhat unlikely=1, unsure=2, somewhat likely=3, very likely=4). We created a binary variable equal to one if participants reported being somewhat or very likely to drive after any number of drinks. We also included a measure of *self-reported driving after drinking*.[3] The study asked participants to report the number of times in the past month that they drove after drinking one to two drinks and three or more drinks in the previous hour. The study collapsed these two measures into a single dichotomous measure to capture any reports of driving after drinking.

2.4 Analysis

Our analyses proceeded in several steps. First, we examined descriptive statistics on personal network characteristics at baseline and follow-up and then estimated fractional logistic models with random effects to assess whether there were significant changes between baseline and follow-up in personal network characteristics. To estimate these models, we created a panel dataset with two observations per participant—one for baseline and one for follow-up. We then regressed each network characteristic on a binary measure of time (follow-up=1), along with a random person-specific intercept to allow for individual variation. Because our dependent variable was a proportion, we used fractional logistic regression rather than ordinary logistic regression; these models are appropriate for fractional outcomes, such as proportions, that range from 0 and 1 (Papke & Wooldridge, 1996). Second, we estimated random effects models to assess whether changes in personal

[3]Only 16 percent of participants had a valid license at 4-month follow-up; however, 70 percent had a valid license at 10-month follow-up. Although individuals without a valid license may have been unwilling to report driving after drinking, the study used several methods to minimize the influence of social desirability, such as using independent interviewers, emphasizing confidentiality, and so on. Despite our efforts, individuals may have under-reported driving after drinking more at baseline than they did at follow-up.

network characteristics (again, measured as proportions) were related to CBT versus UC assignment. Third, we estimated multivariable negative binomial and logistic regression models to determine whether changes in personal network characteristics (measured categorically with response categories equal to –1, 0, 1) were related to binge drinking, drinks per week, intentions to drive after drinking, and self-reported driving after drinking at 4- and 10-month follow-up. In all multivariable models, we controlled for CBT assignment, a continuous measure of age, and binary indicators of gender (male=1) and ethnicity (Hispanic=1).

3. Results

We first assessed whether the composition of social networks changed from baseline to 4-month follow-up. Network characteristics—expressed as average proportions of network members—at baseline and follow-up are reported in Table 1. Table 2 displays the categorical network change measures that we used in our negative binomial and logistic regression models of drinking outcomes. Table 3 reports the results of our random effects models. Four (of eight) aspects of social networks were significantly different between baseline and follow-up. Specifically, participants reduced the proportion of network members with whom they drank from .41 to .30 (coefficient = –.51, $p<.001$), the proportion of network members with whom they drank more alcohol than they wanted from .15 to .07 (coefficient = –1.09, $p<.0001$), and the proportion of network members who would be happy if they reduced drinking and driving from .93 to .88 (coefficient = –1.25, $p<.0001$). Participants increased the proportion of network members who would have supported drinking less from .88 to .93 (coefficient = .70, $p<.001$).

Second, we examined whether social network changes were related to intervention condition—that is, whether participants randomly assigned to receive CBT experienced significant changes in their social networks relative to those receiving UC. We found no significant intervention effect; in other words, participants experienced similar changes in their social networks regardless of whether they received CBT or UC.

Third, we assessed whether social network changes were related to drinking outcomes at follow-up. The results of our negative binomial and logistic regression models examining drinking outcomes at 4-month and 10-month follow-up are displayed in Table 4 and the results of logistic regression models examining self-reported driving after drinking and intentions to drive after drinking at 4- and 10-month follow-up are displayed in Table 5. Results show that changes in several network variables were significantly related to drinking outcomes at either the 4-month or 10-month follow-up.

One network change was associated with drinks per week. Specifically, reductions in the proportion of network members with whom the participant drinks (i.e. drinking partners) was related to fewer drinks per week at 4-month follow-up. None of the network characteristics was significantly associated with drinks per week at 10-month follow-up.

Results showed there was a positive relationship between changes in the proportion of network members with whom the participant drank more alcohol than they wanted to and binge drinking at 10 months. Thus, increasing the proportion of individuals with whom one drank more alcohol than they wanted to over time was associated with greater likelihood of long-term binge drinking, whereas reducing these kinds of network members was associated with lower likelihood of long-term binge drinking. In addition, increasing network members who provided emotional support was associated with reduced likelihood of binge drinking at 4-months.

Only one change in network characteristics was significantly associated with self-reported driving after drinking. Specifically, increasing the proportion of network members with whom the participant drank was associated with greater odds (whereas decreasing these network members was associated with lower odds) of self-reported driving after drinking at 4-month follow-up. No changes in network characteristics were associated with self-reported driving after drinking at 10-month follow-up.

Finally, two changes in network characteristics were associated with intentions to drive after drinking. Increasing the proportion of network members with whom they (the participant) drank was associated with greater likelihood (whereas decreasing these network members was associated with lower likelihood) of intentions to drive after drinking at 4-month follow-up. In addition, changes in the proportion of network members who would have supported drinking at home instead of out was positively associated with 10-month intentions to drive after drinking. Thus, increasing these network members was associated with a greater likelihood of intentions to drive after drinking (whereas decreasing these network members was associated with lower likelihood of intentions to drive after drinking) in the long-term.

4. Discussion

This study recruited participants with a first-time DUI attending three-month DUI programs. Overall, results indicated that individuals in these programs reported several changes in the composition of their social networks between the two weeks prior to their DUI incident and when they ended their program (four months after their baseline interview). Specifically, they significantly reduced the proportion of network members with whom they drank alcohol, those with whom they drank more alcohol than they wanted to, and increased the proportion of network members who would have supported drinking less. These results suggest that individuals attending a first-time DUI program are making important social network changes by reducing risky influences and increasing supportive influences. Surprisingly, participants significantly reduced the proportion of network members who would be happy if they reduced drinking and driving. Although somewhat unexpected, this change was substantively small, and may reflect changes attributable to the participant’s own drinking behaviors (i.e., fewer network members being happy if the participant reduced drinking and driving because they are drinking and driving less).

Our findings also indicated that these network changes were not related to intervention assignment. These results suggest that individuals in the participating DUI programs are changing their social networks in positive ways regardless of intervention assignment. One explanation for this finding may be that the broader DUI experience, including participation in DUI programs and the ramifications of the DUI (e.g., jail time, emotional stress, financial strain, relationship conflict), prompts individuals to make changes to their social networks. Making such changes may be especially true when these networks comprise greater proportions of risky network members, such as drinking partners, which may be likely in the immediate weeks preceding a DUI incident. Certain components of the DUI program, such as group and individual counseling, may assist individuals with a DUI in identifying negative influences and also facilitate relationships with others who are less likely to drink. Future qualitative research may focus on interviewing participants who change and do not change their social networks to identify these change mechanisms.

Our study is the first to our knowledge to examine how changes in social networks over time are associated with changes in drinking outcomes among a first-time DUI population. Overall, we found that reductions in risky networks, such as individuals with whom the participant drank alcohol, were associated with significant reductions in short-term drinking outcomes such as drinks per week, self-reported driving after drinking, and intentions to drive after drinking (whereas increases in drinking partners were associated with increases in these drinking outcomes). These findings are consistent with prior research that shows that drinking partners have an influence on alcohol outcomes (Lau-Barraco, Braitman, Leonard, & Padilla, 2012). Furthermore, increasing supportive network members was associated with decreased binge drinking at 4-month follow-up (whereas decreasing supportive network members was associated with increased binge drinking). Although these changes were not sustained at 10-month follow-up, having an increase in supportive network members may lead to more immediate reductions in the likelihood of binge drinking, which was followed by broader overall declines at 10-month follow-up.

Conversely, reductions in the proportion of network members with whom the participant drank more alcohol than they wanted to was associated with reduced likelihood of participant binge drinking at 10-month follow-up (and increases in these kinds of network members were associated with increased likelihood of binge drinking at 10-month follow-up). This finding is important because binge drinking is associated with DUI recidivism (McCutcheon et al., 2009). Given that these kinds of risky network members are rare—representing only 15% of network members prior to DUI and half that (7%) at 4-month follow-up—and influential, identifying and minimizing the impact of these kinds of network members should be an important clinical priority for preventing DUI and related risk factors.

Somewhat unexpectedly, changes in the proportion of network members who would have supported drinking at home instead of out was positively associated with 10-month intentions to drive after drinking. Although we also expected these network members to be protective, we think it is important to note that changes in proportions of these network members was not associated with actual self-reported driving after drinking. Indeed, prior work has shown that having greater proportions of network members who supported drinking at home instead of out immediately prior to the DUI was associated with fewer alcohol-related problems at the time of the baseline interview (Matsuda et al., 2020). Further research should probe the coping strategies that individuals with DUI use to better understand potential positive and negative consequences.

Our results have implications for DUI interventions, particularly the development of social network interventions. Treatment programs have increasingly used social network interventions, which use network characteristics, network change, or network data to generate desired outcomes, to promote health behaviors and outcomes (Shelton et al., 2019). Originally based on diffusion of innovations theory, these interventions come in a variety of approaches (Valente, 2012) and research has shown them to be generally effective for outcomes such as sexual health (Hunter et al., 2019). Although less common (Shelton et al., 2019), network interventions that rely on an “alteration” approach, which attempts to deliberately alter the network (Valente, 2012), may be particularly beneficial for individuals recovering from alcohol use disorders, who are likely to benefit from changes in their social networks and increased social support (Kelly, 2017). These interventions can utilize visualizations of participant’s social networks to identify problematic and protective influences and target network change by increasing supportive networks and decreasing risky networks associated with high-risk behavior (Kennedy et al., 2018a). A network intervention that provides network visualization may amplify the benefits of evidence-based, individually focused behavior change interventions by also targeting changes to the social environment that may be triggering or enabling the behavior (Kennedy et al., 2018a). For example, a network intervention that paired network visualization with motivational interviewing (MI) found that subsequent network changes were associated with improved substance use outcomes (Kennedy et al., 2018b). These approaches have the potential to increase the efficacy of CBT and related approaches by helping participants recognize risky network members and providing tools to reduce these influences and enhance positive ones. Our findings show that changes in these networks are associated with risk factors for future DUIs and suggest that network interventions that specifically target these mechanisms are worthy of future evaluation. Given that CBT alone does not lead to change in networks, along with the fact that natural changes in networks are associated with differential drinking outcomes, clinical interventions that enhance CBT to focus on network changes are likely to improve the interventions’ impacts.

This study has several limitations. First, our baseline social network data rely on retrospective recall of the two weeks prior to the DUI incident and this may be subject to error, particularly if participants were drinking heavily during this time. Because eligibility in the larger RCT required participants to have had their DUI incident within the past year, the recall length could be as long as one year. Relatedly, both social network surveys rely on retrospective recall as well as participants’ perceptions of their network members. Second, our sample is limited to clients of first-time DUI programs in one California county enrolled in a randomized controlled trial who consented to participate in the network survey and therefore may be of limited generalizability. Prior work showed that participants were less risky at baseline than participants in the overall study (Matsuda et al., 2020). Relatedly, we suffered from the loss of several observations due to a technical error, although this did not appear to bias our sample in any systematic way.

5. Conclusion

Our results indicate that individuals in first-time DUI programs report changes in their networks by reducing risky members and increasing supportive members. Furthermore, decreasing risky members and increasing supportive members over time was associated with improved drinking outcomes. Although we did not find that network changes were attributable to CBT assignment, our results suggest future research might benefit from examination of social network interventions enhanced with CBT and other evidence-based programs that direct participants who do not experience natural changes in their networks to identify and reduce risky network members and identify and increase supportive network members to better promote change.

Acknowledgements

The current study was funded by a grant from the National Institute on Minority Health and Health Disparities (NIMHD; R01MD007762, Principal Investigator: Karen Chan Osilla) and National Institute on Alcohol Abuse and Alcoholism (NIAAA) Grant R01AA019663 (principal investigator: Bing Han). The content is solely the responsibility of the authors and does not necessarily represent the official views of NIMHD, NIAAA, or the National Institutes of Health

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Highlights

- Individuals with a first DUI were surveyed about pre- and post-DUI social networks.
- Participants reduced risky network members and increased supportive network members.
- Random assignment to CBT was unrelated to changes in social networks.
- Reducing drinking partners was associated with improved drinking outcomes.

Table 1:

Descriptive statistics (n=94).

	Baseline M (S.D.) or %	4-month M (S.D.) or %	10-month M (S.D.) or %
Drinking Outcomes			
Drinks Per Week	8.21(S.D.)	8.10 (S.D.)	6.69 (S.D.)
Binge Drinking	39	35	22
Self-reported driving after drinking	18	16	19
Intentions to drive after drinking	52	26	22
Network Characteristics			
Proportion of network members…			
… with whom they drank	0.41	0.30	
… with whom they drank more alcohol than they wanted	0.15	0.07	
… who would be happy if they reduced or stopped drinking	0.55	0.60	
… who would be happy if they reduced drinking and driving	0.93	0.88	
… who would have supported drinking less	0.88	0.93	
… who would have supported drinking at home instead of out	0.87	0.88	
… who provide emotional support	0.68	0.74	
… who provide tangible support	0.44	0.45	

Table 2:

N and % of participants reporting change in network characteristics between baseline and follow-up (n=94).

Proportion of network members…	Increased N (%)	Same N (%)	Decreased N (%)
… with whom they drank	28 (29.79%)	12 (12.77%)	54 (57.45%)
… with whom they drank more alcohol than they wanted	13 (13.83%)	51 (54.26%)	30 (31.91%)
… who would be happy if they reduced or stopped drinking	39 (41.49%)	29 (30.85%)	26 (27.66%)
… who would be happy if they reduced drinking and driving	5 (5.32%)	77 (81.91%)	12 (12.77%)
… who would have supported drinking less	22 (23.40%)	60 (63.83%)	12 (12.77%)
… who would have supported drinking at home instead of out	22 (23.40%)	58 (61.70%)	14 (14.89%)
… who provide emotional support	46 (48.94%)	17 (18.09%)	31 (32.98%)
… who provide tangible support	39 (41.49%)	25 (26.6%)	30 (31.91%)

Table 3:

Random effects panel models assessing change in characteristics of social networks between baseline and follow-up (n=94).

Proportion of network members…	Coefficient	OR	CI
… with whom they drank	-0.51^{**}	.60	.43, .84
… with whom they drank more alcohol than they wanted	-1.09^{***}	.34	.22, .51
… who would be happy if they reduced or stopped drinking	0.23	1.26	.79, 2.01
… who would be happy if they reduced drinking and driving	-1.25^{***}	.29	.16, .52
… who would have supported drinking less	0.70^{**}	2.01	1.23, 3.30
… who would have supported drinking at home instead of out	0.20	1.22	.78, 1.91
… who provide emotional support	0.29	1.34	.90, 1.98
… who provide tangible support	0.03	1.03	.70, 1.53

Each panel model regresses the proportional network measure on a binary measure of time (follow-up=1) and a random intercept

p<.0001***p<.001**p<.05*

Table 4:

Negative binomial and logistic regression models examining association between change in network characteristics and drinks per week, binge drinking.

	Drinks Per Week Relative Risk (CI)		Binge Drinking Odds Ratio (CI)	
Changes in proportion of social network members…	**4-month (n=93)**	**10-month (n=89)**	**4-month (n=94)**	**10-month (n=90)**
… with whom they drank	1.61 (1.20, 2.16) **	1.12 (.85, 1.49)	1.29 (.76, 2.21)	1.28 (.70, 2.33)
… with whom they drank more alcohol than they wanted	1.15 (.77, 1.72)	1.35 (.93, 1.97)	1.16 (.56, 2.43)	2.83 (1.12, 7.14) *
… who would be happy if they reduced or stopped drinking	.89 (.63, 1.26)	1.22 (.90, 1.66)	.63 (.35, 1.16)	.63 (.32, 1.27)
… who would be happy if they reduced drinking and driving	1.17 (.71, 1.94)	1.01 (.61, 1.68)	.66 (.22, 1.96)	.57 (.16, 1.96)
… who would have supported drinking less	1.37 (.91, 2.07)	1.10 (.76, 1.57)	1.34 (.60, 3.02)	.57 (.23, 1.43)
… who would have supported drinking at home instead of out	.98 (.66, 1.45)	.94 (.64, 1.37)	.81 (.37, 1.78)	.99 (.40, 2.45)
… who provide emotional support	.89 (.65, 1.20)	.91 (.69, 1.22)	.56 (.32,.96) *	.81 (.45, 1.47)
… who provide tangible support	1.11 (.82, 1.51)	1.12 (.83, 1.50)	.88 (.50, 1.56)	1.29 (.66, 2.51)

Each model contains a single network change measure and controls for baseline measures of the dependent variable, age (continuous), gender (male=1), ethnicity (Hispanic=1), and CBT assignment

p<.0001***p<.001**p<.05*

Table 5:

Logistic regression models examining association between change in network characteristics and self-reported driving after drinking, intentions to drive after drinking.

	Self-reported driving after drinking Odds Ratio (CI)		Intentions to drive after drinking Odds Ratio (CI)	
Changes in proportion of social network members…	**4-month (n=94)**	**10-month (n=90)**	**4-month (n=94)**	**10-month (n=90)**
… with whom they drank	2.34 (1.18, 4.65) *	1.46 (.80, 2.68)	1.97 (1.10, 3.52) *	1.28 (.70, 2.35)
… with whom they drank more alcohol than they wanted	1.43 (.60, 3.41)	1.31 (.58, 2.99)	1.23 (.56, 2.74)	1.31 (.56, 3.07)
… who would be happy if they reduced or stopped drinking	.83 (.40, 1.75)	1.32 (.65, 2.68)	.82 (.42, 1.58)	.58 (.27, 1.22)
… who would be happy if they reduced drinking and driving	1.18 (.32, 4.43)	1.73 (.46, 6.47)	.69 (.20, 2.31)	.86 (.24, 3.14)
… who would have supported drinking less	1.11 (.41, 2.95)	.60 (.23, 1.54)	.79 (.36, 1.78)	.81 (.35, 1.89)
… who would have supported drinking at home instead of out	1.42 (.56, 3.64)	2.60 (.97, 6.98)	.93 (.39, 2.21)	3.21 (1.12, 9.21) *
… who provide emotional support	.69 (.35, 1.34)	1.14 (.61, 2.13)	.72 (.40, 1.31)	1.13 (.59, 2.18)
… who provide tangible support	1.77 (.82, 3.82)	1.72 (.84, 3.54)	.75 (.39, 1.42)	1.86 (.87, 3.97)

Each model contains a single network change measure and controls for baseline measures of the dependent variable, age (continuous), gender (male=1), ethnicity (Hispanic=1), and CBT assignment

p<.0001***p<.001**p<.05*