179 (2025) 209801

Contents lists available at ScienceDirect

Journal of Substance Use and Addiction Treatment

journal homepage: www.journals.elsevier.com/journal-of-substance-use-and-addiction-treatment

Exploring social connections and mental well-being among members of a sober active community: A social network analysis

Megan S. Patterson [a,b,*], Yunlin Zhou [a,b], Anjorin E. Adeyemi [b,c], Shuai Ma [b,c], Linlin Luo [b], Allison N. Francis [a,b], Zhenning Kang [a,b], Katie M. Heinrich [d], Tyler Prochnow [a,b]

[a] Department of Health Behavior, United States of America
[b] Texas A&M University, United States of America
[c] Department of Agricultural Leadership, Education & Communications, United States of America
[d] The Phoenix, United States of America

ARTICLE INFO

Keywords:
Social network analysis
Addiction recovery
Social networks
Mental health
Psychological distress

ABSTRACT

Introduction: Addiction is a complex and pervasive condition which affects physical, social, and mental health. Research consistently shows that social support and social networks are key to the addiction recovery process (defined as a process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential) and recovery communities available outside of or in conjunction to formal treatment are effective in providing such support. This study investigated social networks and psychological distress among members of *The Phoenix*, a sober active community that incorporates group-based exercise (e.g., CrossFit) into the recovery process.
Methods: Using Social Network Analysis (SNA), we analyzed relationships within *The Phoenix* CrossFit programs in Denver, Colorado (N = 35) and Wichita, Kansas (N = 42). Linear Network Autocorrelation Models (LNAMs) assessed whether social network positions and connections related to psychological distress among members, and Exponential Random Graph Models (ERGMs) explored factors that explained the presence of supportive relationships between *Phoenix* members.
Results: Network centrality, such as being identified as a source of support (i.e., in-degree), was associated with lower psychological distress, while peripheral positions correlated with higher psychological distress in both networks. Additionally, individuals experiencing higher psychological distress tended to seek more supportive connections, whereas those with lower distress were more frequently nominated as supportive figures.
Conclusions: These results highlight the potential of community-based recovery resources like *The Phoenix* to foster social networks that promote mental well-being.

1. Introduction

Addiction is a complex and chronic disorder characterized by a psychological and/or physical dependence on the use of drugs or other substances, or on activities or behaviors such as gambling (Sussman & Sussman, 2011). This widespread issue is linked to numerous adverse physical and mental health struggles (Kelly & Daley, 2013; National Institute on Drug Abuse, 2018; Schulte & Hser, 2013), and while professional treatment and structured programs help people abstain from or manage their addiction, only 25 % of the estimated 40.3 million people who need treatment have access to care (Substance Abuse and Mental Health Services Administration (SAMHSA), 2024). The vast majority of those who do meet criteria for a substance use disorder do not perceive a need for treatment (Substance Abuse and Mental Health Services Administration (SAMHSA), 2024). As such, recovery outside of, or in conjunction to, formal treatment is often necessary.

Recovery is defined as a process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential (Substance Abuse and Mental Health Services (SAMHSA), 2014; The Association for Addiction Professionals

* Corresponding author at: Texas A&M University, United States of America.
E-mail addresses: megpatterson@tamu.edu (M.S. Patterson), versprechen@tamu.edu (Y. Zhou), anjy2@tamu.edu (A.E. Adeyemi), shuai_ma2021@tamu.edu (S. Ma), linlin.luo@tamu.edu (L. Luo), allison.francis@tamu.edu (A.N. Francis), zhenningkang@tamu.edu (Z. Kang), kheinrich@thephoenix.org (K.M. Heinrich), tprochnow@tamu.edu (T. Prochnow).

https://doi.org/10.1016/j.josat.2025.209801
Received 16 January 2025; Received in revised form 7 August 2025; Accepted 4 September 2025
Available online 13 September 2025

(NAADAC), 2024). This journey necessitates overcoming or managing addiction and its symptoms, making informed choices supporting physical and emotional well-being, and establishing stability in crucial life domains such as home, purpose, and community (Substance Abuse and Mental Health Services (SAMHSA), 2014) along a multitude of pathways that may or may not include formal treatment (Kelly et al., 2017).

Psychological distress, which encompasses a spectrum of negative emotional and mental states (i.e., depression, anxiety, stress), is a common struggle for people recovering from addiction and can impede progress towards recovery goals (National Institute on Drug Abuse, 2018). Psychological distress can predate someone's addiction, develop concurrently, or be exacerbated by the demands of the recovery process itself (Erga et al., 2021; Flynn et al., 2004). Achieving the core components of recovery—health, wellness, self-direction, and realizing potential—often hinges on effectively managing and improving psychological distress (Cano et al., 2017; Flynn et al., 2004).

Previous research consistently points to social support and social networks as key components of the recovery process (Best & Lubman, 2017; Kelly et al., 2014). People recovering from addiction who have strong social support systems are less likely to initiate and/or sustain substance use and are more likely to report positive physical and mental health, helping to foster lifelong recovery from addiction (Laitman et al., 2014; McGaffin et al., 2018). Belonging to a network of peers in recovery is among the strongest predictors of sustained remission (Best & Lubman, 2017; Longabaugh et al., 2010). In a study of over 500 people recovering from substance use disorder, shifting from social isolation to social connectedness was a principal factor associated with the transition from addiction to recovery and positive changes in the composition of the individuals' social networks (Bathish et al., 2017). Thus, strengthening perceptions of connectedness to others, and being part of a supportive community composed of peers in and advocates of recovery, are key to building recovery capital for people recovering from addiction.

Given the importance of social connectedness and support on promoting recovery, community-based pathways to recovery have emerged as a critical component of the recovery landscape (Ashford et al., 2021). These approaches span a wide range of settings and formats, from recovery community organizations and recovery community centers to organically formed groups such as 12-step communities where individuals connect around shared goals and experiences (Finch & Karakos, 2014; Jason et al., 2021). A body of longitudinal work investigating social mechanisms of behavior change among Alcoholics Anonymous (AA) participants has found that social network restructuring (i.e., moving from a pro-drinking to a pro-abstinence network), receiving social support and encouragement from peers in recovery, gaining abstinence self-efficacy, and sustained engagement in AA translated to recovery years after formal treatment (Bond et al., 2003; Kelly et al., 2012; Longabaugh et al., 2010). For example, Bond and colleagues assessed the long-term impact of AA involvement and social network characteristics on abstinence 1- and 3-years following treatment for substance use. They found that AA participation in the year prior to follow-up was a significant predictor of 90-day abstinence at both the 1-year and 3-year follow-up assessments. They also found that social networks played a mediating role in the positive relationship between AA participation and abstinence, showing that AA's positive impact on abstinence is, in part, explained by its ability to foster recovery-supportive social networks, particularly those providing AA-specific support for reducing drinking (Bond et al., 2003). Similarly, Longabaugh et al. (2010) explored 90-day abstinence and drinking intensity in a sample of 1726 adults with alcohol use disorder. They specifically looked at how changes in AA involvement at 3-, 9-, and 15-months post-treatment influenced changes in social network characteristics overtime, and whether those things impacted alcohol use. They found that AA facilitates adaptive changes in people's social networks that support abstinence, specifically in terms of reducing pro-drinking social ties within networks (Longabaugh et al., 2010). AA and other community-based models share a common emphasis on offering a sense of belonging, fostering peer support, and promoting holistic well-being for people in recovery (Bahl et al., 2019; Jason et al., 2021). These studies lay the groundwork the importance of social networks and support within community-based recovery support systems.

1.1. *Social Network Analysis*

Social Network Analysis (SNA) is a methodological approach that examines relationships and structures within social networks. SNA examines the relationships and connections among members of a network and how those connections influence individuals' behaviors and access to support and/or resources (Valente, 2010). In shifting analytical focus from the individual to network connections and positions, SNA offers a unique perspective through which to explore the complexities of addiction and mental health (Scott, 2017). By mapping the relationships among individuals within specific community-based recovery pathways, SNA can reveal how social connections might foster (or hinder) recovery-related outcomes, including mental well-being. Moreover, SNA enables researchers to identify key players and resources within social networks, which can be leveraged to provide emotional support, enhance social cohesion, and promote healthier behaviors (Perry et al., 2018).

1.2. *The Phoenix*

The Phoenix is a national community-based recovery support, specifically a sober active community, that leverages the power of community to support individuals impacted by substance use disorders and mental health challenges (The Phoenix, 2024). Their focus is on building a sense of community and belonging, both of which are crucial for recovery (Bahl et al., 2019; Cano et al., 2017). Due to copious research in support of physical activity as an aid in the addiction recovery process (Patterson et al., 2022b), *The Phoenix* prioritizes events that promote physical activity and active lifestyles with others. *The Phoenix* offers hundreds of weekly sober events and activities (e.g., CrossFit, yoga, biking), both in-person and online, creating safe spaces for individuals to connect, find support, and experience psychological safety. Most of these events are volunteer led and are hosted in partnership with existing community spaces or in a few facilities owned by *The Phoenix*. While participants must be 48-h sober from any non-prescription substances to participate, all programming offered through *The Phoenix* is at no cost to the participant (The Phoenix, 2024).

While *The Phoenix* offers a range of programs across the United States, this study will focus on two locations that offer CrossFit programs to their participants — Denver, Colorado and Wichita, Kansas. We chose to focus on CrossFit for three main reasons: (1) it is known for creating social connections and community among participants (Lautner et al., 2021; Patterson et al., 2020; Patterson et al., 2022a); (2) it is an exercise program that offers the physical activity benefits useful for addiction recovery (Heinrich et al., 2014; Lautner et al., 2020), and (3) because it offers a natural network of people to conduct a social network analysis (SNA). Denver and Wichita were selected because they both have *Phoenix*-owned CrossFit gyms that only serve *Phoenix* members, as opposed to CrossFit affiliates which incorporate *Phoenix* classes into their existing programming and serve both *Phoenix* members and local gym members.

1.3. *The current study*

The purpose of this study is to use Social Network Analysis (SNA) to examine the association between social support and psychological distress among *Phoenix* members active in the Denver and Wichita CrossFit programs. The following research questions (RQs) and hypotheses drove our analyses:

1. RQ1: *Is social network position (e.g., degree centrality) within the Denver and Wichita CrossFit networks related to the level of psychological distress reported among Phoenix members?* We expect that *Phoenix* members who are more central, and therefore more connected within their networks, will report less psychological distress than more peripheral network members. Additionally, we hypothesize that those who more frequently attend *Phoenix* programming and those who have higher physical activity scores will also report less psychological distress.
2. RQ2: *What is associated with the presence of supportive social ties between members of The Phoenix in Denver and Wichita?* We expect that people with lower psychological distress are more likely to send and receive supportive ties within their networks. We also expect higher physical activity scores and more frequent attendance at *Phoenix* programming will be related to more social connections within the Denver and Wichita networks.

2. Methods

2.1. Participants and procedures

Prior to data collection, researchers partnered with *Phoenix* staff and stakeholders to define membership to the Denver and Wichita networks. Network membership was defined as anyone in the Denver or Wichita locations that (1) attended a CrossFit class at least once in the past 30 days and (2) on average, attends classes at least once per week. Each person who met these criteria were included on a roster for each location. All members on the Denver and Wichita rosters received an email from *The Phoenix* describing the study purpose and an invitation to participate in an online survey. The Denver roster contained 45 people, 35 of which participated in the study (77.8 % response rate) and the Wichita roster contained 53 people, 42 of which participated in the study (79.2 % response rate). After giving their electronic consent, participants answered questions measuring demographic variables, attribute variables (i.e., physical activity scores), and social networks. Participants were sent a $40 Amazon gift card upon completion of their survey. All study procedures were approved by the institutional review board prior to data collection.

A sociocentric network design assessed social relationships within both locations, and how they related to psychological distress scores among participants. Sociocentric network analysis (i.e., whole network analysis) requires the assessment of all members within a defined, bounded group and involves either permutation testing or randomization/simulation testing for analysis, where observed data matrices are compared to thousands of either permutated or simulated matrices to create a sample distribution and determine statistical probability of observed effects (Leenders, 2002; Snijders et al., 2010). As such, a strong response rate is needed to accurately compare observed to generated data (Borgatti et al., 2018; Snijders et al., 2010). Previous sociocentric network research suggests a 60 % response rate from a defined network yields adequate representation of the observed network to conduct analyses (Borgatti et al., 2006; Costenbader & Valente, 2003; Marks et al., 2013). Both locations met this requirement.

2.2. Measures

2.2.1. Demographic/background information

Participants indicated their age (in years) at the time of survey completion, gender (open response, coded into man = 0, woman = 1, other = 2), and race/ethnicity (1 = white, 2 = Black/African American, 3 = Hispanic, 4 = Asian, Pacific Islander, 5 = Indigenous Person, Native American, Hawaiian Native, 6 = Multiracial, 7 = Other, 8 = Prefer not to say).

2.2.2. Psychological distress

The Kessler Psychological Distress Scale (K6) is a 6-item self-report instrument designed to measure non-specific psychological distress (Kessler et al., 2002). Using a 5-point Likert scale ranging from "none of the time" to "all of the time" K6 questions ask respondents to indicate how often they felt: (1) nervous, (2) hopeless, (3) restless or fidgety, (4) so depressed that nothing could cheer them up, (5) that everything was an effort, and (6) worthless over the past 30 days. Higher scores indicate greater psychological distress (Kessler et al., 2002). Previous studies using the K6 have reported generally strong internal consistency reliability, with Cronbach's alphas ranging from 0.69 to 0.92; see review by (Mewton et al., 2016). Our study returned a Cronbach's alpha of 0.82.

2.2.3. Program adherence

Participants self-reported the average number of CrossFit classes they attended weekly at their respective *Phoenix* location, with response options 0 = less than once per week, 1 = once per week, 2 = twice per week, 3 = three times per week, 4 = four times per week, 5 = five times per week, and 6 = more than five times per week.

2.2.4. Leisure-time exercise

The Godin Leisure-Time Exercise Questionnaire (Godin LTEQ) was used to assess participants' self-reported levels of leisure-time exercise participation (Godin & Shephard, 1985). The Godin LTEQ asks respondents to report the number of times per week they engage in strenuous, moderate, and mild exercise for at least 15 min per session. A total Godin LTEQ score is calculated by multiplying strenuous exercise by 9, moderate exercise by 5, and mild exercise by 3, and summing the products into a single score. Scores of 24 or higher typically indicate someone is highly active and likely to experience health benefits from their exercise engagement (Godin, 2011).

2.2.5. Sociometric network data and network variables

Participants answered a network generator question, where they selected from their location's roster all other *Phoenix* members that they felt "go above and beyond to support them." They asked to select "all that apply" but not to select themselves.

Using network generator data, we calculated three network measures: in-degree, out-degree, and closeness. In this study, in-degree specifically represents the frequency to which a person was chosen as someone who goes above and beyond to support another *Phoenix* member. Conversely, out-degree reflects the number of people within *The Phoenix* a member feels goes above and beyond to support them. Closeness is a measure of distance from all other members of the network, with higher closeness scores revealing greater distance from other network members. The higher someone's closeness score, the more peripheral they are in their network (Freeman, 1979). Each member of the network received their own in-degree, out-degree, and closeness score.

2.3. Analytic strategy

We calculated descriptive statistics for both *Phoenix* locations in R Studio (R Core Team, 2024). Linear network autocorrelation models (LNAMs) analyzed the relationship between network connections and psychological distress scores while accounting for demographic information, program adherence, and Godin LTEQ scores. Network autocorrelation modeling is a form of regression analysis that uses permutation testing to account for the interdependent nature of network data. LNAMs determine the role network influences and connections may play in explaining specific outcome variables (Leenders, 2002). LNAMs return an autocorrelation parameter known as a network effect, which indicates how much the outcomes of individuals are influenced by their connections within the network (Leenders, 2002). LNAMs predicting psychological distress scores were conducted for the Denver and Wichita networks, and estimates were determined significant at the $p < 0.05$ level.

In addition to LNAMs, we used exponential random graph models

(ERGMs) to determine significant factors associated with the presence of supportive social connections between *Phoenix* members in Denver and Wichita (Lusher et al., 2013). ERGMs use iterative Marcov Chain Monte Carlo algorithms to approximate the maximum likelihood estimates for the associations between a set of parameters and tie presence (Lusher et al., 2013). ERGMs return parameter estimates (PE) and standard errors (SE) for each factor entered in the model. These PEs are approximate log-odds representing increases or decreases in the probability of a tie existing between two people. A parameter is deemed significant at the $p < 0.05$ level when the PE is greater than two times the SE (Robins et al., 2007). LNAM and ERGM analyses were completed using the "statnet" package (Handcock et al., 2003) in R. A network visualization (see Fig. 1 in the Discussion) was created using Gephi (Bastian et al., 2009).

2.3.1. *Model specification*

We used the same set of variables in both LNAMs, and the same set of parameters in both ERGMs. Independent variables in the LNAMs included: age, gender (reference woman), program adherence, Godin LTEQ scores, in-degree, out-degree, closeness, and network effects. For ERGMs, network structure parameters included density (edges or connections in the network), reciprocity (connections that are mutually shared between two individuals), and transitivity (three individuals connected to each other). Nondirectional covariates, including age, program adherence, and physical activity, and a parameter assessing homophily based on gender (i.e., whether two people are the same gender) were included to assess if these variables related to increased odds of someone having a supportive social connection within the network. Finally, sender and receiver covariates were added for psychological distress scores. These parameters assess the likelihood of incoming or outgoing ties with the increase (or decrease) in value for each variable. In this case, we assessed the association between greater psychological distress and a person sending connections, as well as a person receiving connections, within both networks.

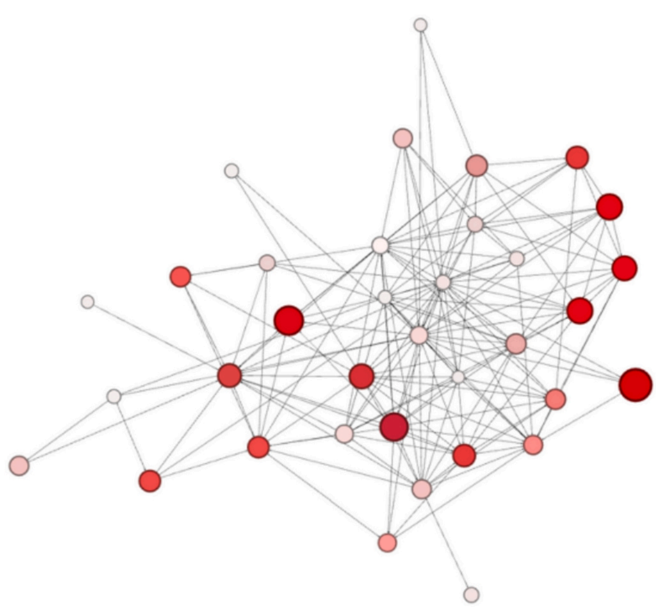

Fig. 1. Network Graph representing Phoenix members and the ties among them. Circles are adjusted based on color and size according to psychological distress score, where darker and larger nodes reveal greater psychological distress.

3. Results

3.1. *Descriptive statistics*

3.1.1. *Denver*

The observed network in Denver consisted of 35 members and 211 supportive social ties among network members. Denver members reported an average in-degree score of 6.03 (SD = 5.93), out-degree also of 6.03 (SD = 3.91), and closeness score of 0.55 (SD = 0.09). The average age of network members in Denver was 38.26 years (SD = 6.41), and 62.9 % (n = 22) identified as men. Most members (62.9 %, n = 22) attended CrossFit classes a minimum of 3–4 times per week, and the network reported high activity levels, on average ($M_{\text{Godin LTEQ}} = 63.51$, SD = 33.83). Members of Denver reported average psychological distress scores of 6.40 (SD = 4.57, range = 0–15).

3.1.2. *Wichita*

The observed network in Wichita consisted of 42 members and 206 supportive social ties among network members. Members reported an average in-degree score of 6.75 (SD = 5.14), out-degree of 4.91 (SD = 3.35), and closeness score of 0.47 (SD = 0.09). Wichita members were 36.69 years old, on average (SD = 9.67), and 50.0 % (n = 21) identified as men. A third of members in Wichita (33.4 %, n = 14) attended CrossFit classes a minimum of 3–4 times per week, and the network reported high activity levels, on average ($M_{\text{Godin LTEQ}} = 56.38$, SD = 25.32). Wichita members reported average psychological distress scores of 6.78 (SD = 4.52, range = 0–19). See Table 1 for all descriptive results for Denver and Wichita.

3.2. *Linear network autocorrelation models*

3.2.1. *Denver*

The Denver LNAM explained 22.4 % of the variance in members' psychological distress scores. In-degree (β = −0.446, SE = 0.169) was negatively associated with psychological distress, whereas closeness (i.e., having greater distance from others in the network; β = 34.456, SE = 14.287) was positively associated with psychological distress scores in this network.

Table 1
Descriptive statistics for Denver and Wichita networks.

	Denver		Wichita	
	Mean ± SD	%, n	Mean ± SD	%, n
Age	38.26 ± 6.41		36.69 ± 9.67	
Gender				
Female		37.1, 13		50.0, 21
Male		62.9, 22		45.2, 19
No answer		0		4.8, 2
Program adherence				
<1×/week		0		9.5, 4
1–2×/week		37.1, 13		57.1, 24
3–4×/week		51.4, 18		28.6, 12
5+×/week		11.5, 4		4.8, 2
Physical activity	63.51 ± 33.83		56.38 ± 25.32	
Psychological distress	6.40 ± 4.57		6.78 ± 4.52	
Network descriptives				
Nodes	35		42	
Edges	211		206	
Degree	12.06 ± 7.81		9.81 ± 7.18	
In-degree	6.03 ± 5.93		6.75 ± 5.14	
Out-degree	6.03 ± 3.91		4.91 ± 3.35	
Closeness	0.55 ± 0.09		0.47 ± 0.09	

3.2.2. Wichita

The LNAM from Wichita explained 25.7 % of the variance in members' psychological distress scores. In-degree (β = −0.458, SE = 0.149) was negatively associated with psychological distress, while having greater distance from others in the network (i.e., closeness; β = 34.573, SE = 8.058) was positively associated with psychological distress scores in Wichita. See Table 2 for all LNAM results.

3.3. Exponential random graph models

3.3.1. Denver

Structural properties including reciprocity (PE = 1.169, SE = 0.262) and transitivity (PE = 0.942, SE = 0.262) increased the odds of a tie being present between members of the Denver network, which indicates that supportive ties were likely mutual (i.e., if person A found person B supportive, person B was also likely to find person A supportive), and that supportive ties likely existed in clusters of network members (i.e., groups of friends likely supported one another). Denver members were more likely to connect with others of the same gender (gender homophily; PE = 0.278, SE = 0.127). Psychological distress was associated with sending and receiving ties in Denver, with higher psychological distress associated with nominating more supportive ties (sender effect; PE = 0.058, SE = 0.016), and lower psychological distress scores associated with receiving more nominations from others (receiver effect; PE = −0.054, SE = 0.016).

3.3.2. Wichita

Structural properties including reciprocity (PE = 1.654, SE = 0.257) and transitivity (PE = 1.135, SE = 0.159) increased the odds of a tie being present between members of the Wichita network. The only other significant parameter was the receiver effect based on psychological distress, which like Denver found that people with lower psychological distress scores were more likely to be nominated as someone who goes above and beyond to support others (PE = −0.039, SE = 0.010). All parameter estimates and standard errors from ERGMs can be found in Table 3.

4. Discussion

The purpose of this study was to assess the relationship between social networks and psychological distress among members of *The Phoenix* in Denver and Wichita participating in CrossFit classes. Using SNA, we specifically examined social network positions related to psychological distress among *Phoenix* members (RQ1) and explored what is associated with the presence of supportive social ties between members (RQ2). Our study found that network position, specifically measured by greater in-degree and greater distance from others in the network (i.e., higher closeness), related to psychological distress scores among *Phoenix* members in both locations, and that psychological distress associated with sending and receiving supportive social ties within *Phoenix* networks.

Table 2
Linear network autocorrelation models explaining psychological distress in Denver and Wichita networks.

Covariate	Denver: $R^2 = 0.224$		Wichita: $R^2 = 0.257$	
	β	SE	β	SE
Age	−0.201	0.107	−0.087	0.079
Gender (ref: woman)	−1.624	1.661	0.591	0.775
Program adherence	−0.404	1.128	0.570	1.185
Physical activity	0.001	1.158	−0.029	0.028
In-degree	−0.446**	0.169	−0.458**	0.149
Out-degree	−0.076	0.531	−0.264	0.271
Closeness	34.456*	14.288	34.573***	8.058
Network effects	−0.004	0.078	−0.059	0.033

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 3
Exponential random graph models assessing factors related to presence of social support ties in Denver and Wichita networks.

Parameter	Denver		Wichita	
	Estimate	SE	Estimate	SE
Structural				
Edges	−3.032***	0.573	−3.635***	0.378
Reciprocity	1.169***	0.262	1.654***	0.256
Transitivity	0.942***	0.127	1.135***	0.158
Homophily				
Gender	0.278*	0.138	0.123	0.136
Non-directional covariates				
Age	−0.015*	0.006	0.008	0.006
Program adherence	0.026	0.049	−0.112	0.079
Physical activity	−0.001	0.001	−0.001	0.001
Sender/receiver covariates				
Psychological distress (incoming; receiver effect)	−0.058***	0.016	−0.039**	0.010
Psychological distress (outgoing; sender effect)	0.050**	0.015	−0.029	0.020

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

4.1. Network position and mental well-being (RQ1)

In-degree—a network position commonly associated with popularity (Freeman, 1979) and in this study meant being recognized as a supportive individual within a recovery community—was negatively related to psychological distress scores in both networks. Lower psychological distress, and mental well-being in general, is closely associated with social connectedness, popularity, and leadership within social networks, suggesting that individuals with less psychological distress are more likely to be in central, influential positions (Holt-Lunstad, 2024; Tracy & Wallace, 2016). Research supports the idea that individuals with stable mental health often take on these central roles within peer support networks, where they influence others and foster network resilience (Tracy & Wallace, 2016). As such, having lower psychological distress scores may create opportunities to hold more central positions within locations of *The Phoenix*.

Conversely, it may be that being central and well connected within the network yields the social support and capital needed to reduce psychological distress. For example, Kawachi and Berkman (2001) found that social ties positively influence mental health through two mechanisms: the main effect model, where social connections broadly enhance psychological well-being, and the stress-buffering model, where they mitigate the impact of stress. In both models, being more central and connected within a network translates to positive mental well-being. In their study on loneliness and mental health, Haslam et al. (2022) found that belonging to meaningful groups provides individuals with a sense of purpose, support, and shared efficacy, which is vital for mental well-being, whereas social disconnection results in loneliness and reduced resiliency. In sum, it was unsurprising that lower psychological distress related to centrality in these networks, both because those who are mentally healthy are likely to occupy such positions in networks, and because central positions offer resources and support that foster improved mental well-being.

Relatedly, *Phoenix* members who were more distant from others in the network, and therefore held more peripheral positions in the network as measured by closeness, had higher psychological distress scores in Denver and Wichita (see Fig. 1). Several studies have shown that being peripheral within a network is related to loneliness, depression, and mental distress (McKenzie et al., 2018; Na et al., 2023; Santini et al., 2020), and that feelings of depression or anxiety may preclude someone from integrating seamlessly within communities and forming new connections (Kleinberg et al., 2013; Maulik et al., 2010). These results suggest that creating connections in these networks could potentially foster mental well-being for participants. Given the importance of social support and connections for successful recovery (Bathish et al., 2017; Kelly et al., 2014; McGaffin et al., 2018) and the already heightened risk for mental distress that is correlated with overcoming an addiction (Substance Abuse and Mental Health Services Administration (SAMHSA), 2024), it is important to prioritize social integration and community engagement to support recovery and mental well-being.

4.2. *Explaining supportive ties (RQ2)*

We found that *Phoenix* members with higher psychological distress nominated more people in their networks that go above and beyond to support them (i.e., sender effects). This aligns with previous research that shows belonging to a supportive community creates opportunities for support seeking across network members and that connecting within social networks fosters a sense of belonging and a shared social identity, both of which are crucial for positive mental health (Allen et al., 2021). Moreover, individuals engaged in supportive communities or networks are more inclined to seek help or support (Kim et al., 2015; Suka et al., 2016).

Like LNAM results, ERGMs also suggested that *Phoenix* members with lower psychological distress scores were more likely to be deemed supportive in their network (i.e., receiver effects). This trend indicates that people experiencing mental well-being may have a greater capacity to provide support, making them valuable resources for others seeking assistance in recovery. Research on recovery capital—a framework that includes personal, social, and community resources supporting recovery—suggests that mental health stability is an important resource for sustaining recovery (Groshkova et al., 2013). In this context, individuals with strong recovery capital, including mental stability, are often perceived as reliable sources of support, which can reinforce their supportive roles in communities (Tracy & Wallace, 2016). This relationship between mental health stability and supportive roles indicates how individuals with lower psychological distress can play a key role in building the supportive network needed within community-based recovery pathways.

Our findings also indicate that individuals who attended more CrossFit classes at their *Phoenix* location were more likely to benefit from its supportive structure. It is possible that engagement with *The Phoenix* not only improves participants' mental health (Paluska & Schwenk, 2000) but also fosters social connections that allow them to be influential members and support more peripheral members (Kelly et al., 2017; Valente & Davis, 1999). Organizations like *The Phoenix* could encourage central members to take on key supportive roles, thereby mitigating the isolation and distress often experienced by peripheral participants.

4.3. *Implications for future research and practice*

This study was an important first step in establishing a relationship between social positions and connections and psychological distress within a two locations of *The Phoenix* sober active community. However, it is important to note that other unmeasured variables may partly explain our findings. For example, we did not assess how long someone has been in recovery, which influences not only their duration and frequency of engagement with *The Phoenix*, and subsequently their network position, but also could directly impact their level of psychological distress. Future research should employ a longitudinal design to assess the coevolution of social connectedness and mental well-being and consider how long someone has been in recovery as part of the analysis. More research is needed to better understand whether social connectedness promotes mental well-being, or initial mental well-being determines group members' social positions and connectedness. Additionally, research in other community-based recovery pathways outside *The Phoenix* could confirm whether similar patterns hold across networks.

This research provides important target points for health professionals to assist the recovery process for members of community-based recovery pathways. First, fostering social connections among program members could have a positive impact on mental well-being. Therefore, recovery programs and communities may encourage social connections and create opportunities (e.g., picnics, game corners, group-based exercise) for members to connect. While more research is needed, our study provides early evidence that programs like *The Phoenix* could be a safe space for people in recovery to find the support provision and social connection they need. The findings showed that psychological distress was associated with higher outgoing nominations, which indicates that *Phoenix* members in these measured networks felt comfortable reaching out for help. Connecting people in recovery in this kind of program may create a sense of community that promotes help-seeking and mental well-being. Similarly, this study found that as people become more central and/or hold positions of influence within their network, they had the capacity to connect with and support others. Therefore, health professionals and program designers may provide training and resources for these key network members as they may be more sought after for support provision. Furthermore, these members' well-connectedness may also improve their own mental well-being, which increases their capacity to support themselves and others.

4.4. *Limitations*

There are a few limitations important to consider when interpreting results from this study. First, despite assessing results from two *Phoenix* locations and general alignment of our findings with social network literature, generalizability is cautioned outside the study networks, especially onto other community-based recovery resources that function differently than *The Phoenix*. And, given the small and select networks analyzed, results have limited and unknown generalizability outside this study. Secondly, these are cross-sectional data, limiting any sort of causal inference. As mentioned above, longitudinal research is needed to better understand how the relationship between social support and psychological distress works overtime. And finally, while we are confident our response rates were strong enough to yield accurate results from permutation testing via LNAMs and simulation models via ERGMs, we did not have complete representation from either network, which means it is possible important social connections were not captured in observed data.

5. Conclusion

Using SNA, this study demonstrated an association between social network position, support, and psychological distress among members of two sober active communities. Our findings highlight the relationship between network centrality and positive mental health, and how psychological distress may impact the odds of someone experiencing social support within their community.

CRediT authorship contribution statement

Megan S. Patterson: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yunlin Zhou:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Anjorin E. Adeyemi:** Writing – review & editing, Writing – original draft, Formal analysis. **Shuai Ma:** Writing –

review & editing, Writing – original draft, Formal analysis. **Linlin Luo:** Writing – original draft, Formal analysis. **Allison N. Francis:** Writing – review & editing, Project administration, Formal analysis, Data curation. **Zhenning Kang:** Writing – review & editing, Writing – original draft. **Katie M. Heinrich:** Writing – review & editing, Data curation, Conceptualization. **Tyler Prochnow:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare financial support for this study provided by Texas A&M Health Science Center Seedling Grant program. There are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Allen, K.-A., Kern, M. L., Rozek, C. S., McInerney, D. M., & Slavich, G. M. (2021). Belonging: A review of conceptual issues, an integrative framework, and directions for future research. *Australian Journal of Psychology, 73*(1), 87–102. https://doi.org/10.1080/00049530.2021.1883409

Ashford, R. D., Brown, A., Canode, B., Sledd, A., Potter, J. S., & Bergman, B. G. (2021). Peer-based recovery support services delivered at recovery community organizations: Predictors of improvements in individual recovery capital. *Addictive Behaviors, 119*, Article 106945. https://doi.org/10.1016/j.addbeh.2021.106945

Bahl, N. K. H., Nafstad, H. E., Blakar, R. M., Landheim, A. S., & Brodahl, M. (2019). Multiple senses of community and recovery processes. A pilot study for a national evaluation of the experiences of persons with substance use problems receiving help and services from Norwegian municipalities. *Journal of Community Psychology, 47*(6), 1399–1418. https://doi.org/10.1002/jcop.22194

Bastian, M., Heymann, S., & Jacomy, M. (2009). *Gephi: An open source software for exploring and manipulating networks* [Computer software].

Bathish, R., Best, D., Savic, M., Beckwith, M., Mackenzie, J., & Lubman, D. I. (2017). "Is it me or should my friends take the credit?" The role of social networks and social identity in recovery from addiction. *Journal of Applied Social Psychology, 47*(1), 35–46. https://doi.org/10.1111/jasp.12420

Best, D., & Lubman, D. (2017). Friends matter but so does their substance use: The impact of social networks on substance use, offending and wellbeing among young people attending specialist alcohol and drug treatment services. *Drugs Education, Prevention and Policy, 24*(1), 111–117. https://doi.org/10.3109/09687637.2016.1149148

Bond, J., Kaskutas, L. A., & Weisner, C. (2003). The persistent influence of social networks and alcoholics anonymous on abstinence. *Journal of Studies on Alcohol, 64*(4), 579–588. https://doi.org/10.15288/jsa.2003.64.579

Borgatti, S. P., Carley, K. M., & Krackhardt, D. (2006). On the robustness of centrality measures under conditions of imperfect data. *Social Networks, 28*(2), 124–136. https://doi.org/10.1016/j.socnet.2005.05.001

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2018). *Analyzing social networks* (2nd ed.). SAGE.

Cano, I., Best, D., Edwards, M., & Lehman, J. (2017). Recovery capital pathways: Modelling the components of recovery wellbeing. *Drug and Alcohol Dependence, 181*, 11–19. https://doi.org/10.1016/j.drugalcdep.2017.09.002

Costenbader, E., & Valente, T. W. (2003). The stability of centrality measures when networks are sampled. *Social Networks, 25*(4), 283–307. https://doi.org/10.1016/S0378-8733(03)00012-1

Erga, A. H., Hønsi, A., Anda-Ågotnes, L. G., Nesvåg, S., Hesse, M., & Hagen, E. (2021). Trajectories of psychological distress during recovery from polysubstance use disorder. *Addiction Research & Theory, 29*(1), 64–71. https://doi.org/10.1080/16066359.2020.1730822

Finch, A. J., & Karakos, H. L. (2014). Substance abuse recovery and schooling: The role of recovery high schools and collegiate recovery communities. *Peabody Journal of Education, 89*(2), 159–164.

Flynn, H. A., Walton, M. A., Curran, G. M., Blow, F. C., & Knutzen, S. (2004). Psychological distress and return to substance use two years following treatment. *Substance Use & Misuse, 39*(6), 885–910. https://doi.org/10.1081/JA-120030892

Freeman, L. (1979). Centrality in social networks: Conceptual clarification. *Social Networks, 1*, 215–239.

Godin, G. (2011). Commentary: The Godin-Shephard leisure-time physical activity questionnaire. *Health and Fitness Journal of Canada, 4*(1).

Godin, G., & Shephard, R. J. (1985). A simple method to assess exercise behavior in the community. *Canadian Journal of Applied Sport Sciences, 10*, 141–146.

Groshkova, T., Best, D., & White, W. (2013). The assessment of recovery capital: Properties and psychometrics of a measure of addiction recovery strengths. *Drug and Alcohol Review, 32*(2), 187–194. https://doi.org/10.1111/j.1465-3362.2012.00489.x

Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., & Morris, M. (2003). statnet: Software tools for the statistical modeling of network data [Computer software]. http://statnetproject.org.

Haslam, S. A., Haslam, C., Cruwys, T., Jetten, J., Bentley, S. V., Fong, P., & Steffens, N. K. (2022). Social identity makes group-based social connection possible: Implications for loneliness and mental health. *Current Opinion in Psychology, 43*, 161–165. https://doi.org/10.1016/j.copsyc.2021.07.013

Heinrich, K. M., Patel, P. M., O'Neal, J. L., & Heinrich, B. S. (2014). High-intensity compared to moderate-intensity training for exercise initiation, enjoyment, adherence, and intentions: An intervention study. *BMC Public Health, 14*(1), 789. https://doi.org/10.1186/1471-2458-14-789

Holt-Lunstad, J. (2024). Social connection as a critical factor for mental and physical health: Evidence, trends, challenges, and future implications. *World Psychiatry, 23*(3), 312–332. https://doi.org/10.1002/wps.21224

Jason, L. A., Saloman-Amend, M., Guerroro, M., Bobak, T., O'Brien, J., & Soto-Nevarez, A. (2021). The emergence, role, and impact of recovery support services. *Alcohol Research: Current Reviews, 41*(1), Article 04. https://doi.org/10.35946/arcr.v41.1.04

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health, 78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Kelly, J. F., Bergman, B., Hoeppner, B. B., Vilsaint, C., & White, W. L. (2017). Prevalence and pathways of recovery from drug and alcohol problems in the United States population: Implications for practice, research, and policy. *Drug and Alcohol Dependence, 181*, 162–169. https://doi.org/10.1016/j.drugalcdep.2017.09.028

Kelly, J. F., Hoeppner, B., Stout, R. L., & Pagano, M. (2012). Determining the relative importance of the mechanisms of behavior change within alcoholics anonymous: A multiple mediator analysis. *Addiction, 107*(2), 289–299. https://doi.org/10.1111/j.1360-0443.2011.03593.x

Kelly, J. F., Stout, R. L., Greene, M. C., & Slaymaker, V. (2014). Young adults, social networks, and addiction recovery: Post treatment changes in social ties and their role as a mediator of 12-step participation. *PLoS One, 9*(6), Article e100121. https://doi.org/10.1371/journal.pone.0100121

Kelly, T. M., & Daley, D. C. (2013). Integrated treatment of substance use and psychiatric disorders. *Social Work in Public Health, 28*(3–4), 388–406. https://doi.org/10.1080/19371918.2013.774673

Kessler, R. C., Andrews, G., Colpe, L. J., Hiripi, E., Mroczek, D. K., Normand, S. L., Walters, E. E., & Zaslavsky, A. M. (2002). Short screening scales to monitor population prevalences and trends in non-specific psychological distress. *Psychological Medicine, 32*(6), 959–976. https://doi.org/10.1017/S0033291702006074

Kim, J. L., Cho, J., Park, S., & Park, E.-C. (2015). Depression symptom and professional mental health service use. *BMC Psychiatry, 15*(1), 261. https://doi.org/10.1186/s12888-015-0646-z

Kleinberg, A., Aluoja, A., & Vasar, V. (2013). Social support in depression: Structural and functional factors, perceived control and help-seeking. *Epidemiology and Psychiatric Sciences, 22*(4), 345–353. https://doi.org/10.1017/S2045796013000504

Laitman, L., Kachu-Karavites, B., & Stewart, L. P. (2014). Building, engaging, and sustaining a continuum of care from harm reduction to recovery support: The Rutgers Alcohol and Other Drug Assistance Program. *Journal of Social Work Practice in the Addictions, 14*(1), 64–83. https://doi.org/10.1080/1533256X.2014.872010

Lautner, S. C., Patterson, M. S., Ramirez, M., & Heinrich, K. (2020). Can CrossFit aid in addiction recovery? An exploratory media analysis of popular press. *Mental Health and Social Inclusion, 24*(2), 97–104. https://doi.org/10.1108/MHSI-02-2020-0007

Lautner, S. C., Patterson, M. S., Spadine, M. N., Boswell, T. G., & Heinrich, K. M. (2021). Exploring the social side of CrossFit: A qualitative study. *Mental Health and Social Inclusion, 25*(1), 63–75. https://doi.org/10.1108/MHSI-08-2020-0051

Leenders, R. T. A. J. (2002). Modeling social influence through network autocorrelation: Constructing the weight matrix. *Social Networks, 24*(1), 21–47. https://doi.org/10.1016/S0378-8733(01)00049-1

Longabaugh, R., Wirtz, P. W., Zywiak, W. H., & O'malley, S. S. (2010). Network support as a prognostic indicator of drinking outcomes: The COMBINE study. *Journal of Studies on Alcohol and Drugs, 71*(6), 837–846. https://doi.org/10.15288/jsad.2010.71.837

Lusher, D., Koskinen, J., & Robins, G. (Eds.). (2013). *Exponential random graph models for social networks: Theory, methods, and applications*. Cambridge University Press.

Marks, P. E. L., Babcock, B., Cillessen, A. H. N., & Crick, N. R. (2013). The effects of participation rate on the internal reliability of peer nomination measures: Participation and sociometric reliability. *Social Development, 22*(3), 609–622. https://doi.org/10.1111/j.1467-9507.2012.00661.x

Maulik, P. K., Eaton, W. W., & Bradshaw, C. P. (2010). The effect of social networks and social support on common mental disorders following specific life events. *Acta Psychiatrica Scandinavica, 122*(2), 118–128. https://doi.org/10.1111/j.1600-0447.2009.1511.x

McGaffin, B. J., Deane, F. P., Kelly, P. J., & Blackman, R. J. (2018). Social support and mental health during recovery from drug and alcohol problems. *Addiction Research & Theory, 26*(5), 386–395. https://doi.org/10.1080/16066359.2017.1421178

McKenzie, S. K., Collings, S., Jenkin, G., & River, J. (2018). Masculinity, social connectedness, and mental health: Men's diverse patterns of practice. *American Journal of Men's Health, 12*(5), 1247–1261. https://doi.org/10.1177/1557988318772732

Mewton, L., Kessler, R. C., Slade, T., Hobbs, M. J., Brownhill, L., Birrell, L., … Andrews, G. (2016). The psychometric properties of the Kessler Psychological Distress Scale (K6) in a general population sample of adolescents. *Psychological Assessment, 28*(10), 1232–1242. https://doi.org/10.1037/pas0000239

Na, P. J., Jeste, D. V., & Pietrzak, R. H. (2023). Social disconnection as a global behavioral epidemic—A call to action about a major health risk factor. *JAMA Psychiatry, 80*(2), 101. https://doi.org/10.1001/jamapsychiatry.2022.4162

National Institute on Drug Abuse. (2018). Common comorbidities with substance use disorders. https://www.drugabuse.gov/node/pdf/1155/common-comorbidities-with-substance-use-disorders.

Paluska, S. A., & Schwenk, T. L. (2000). Physical activity and mental health: Current concepts. *Sports Medicine (Auckland, N.Z.), 29*(3), 167–180. https://doi.org/10.2165/00007256-200029030-00003

Patterson, M. S., Amo, C. E., Prochnow, T., & Heinrich, K. M. (2022a). Exploring social networks relative to various types of exercise self-efficacy within CrossFit participants. *International Journal of Sport and Exercise Psychology, 20*(6), 1691–1710. https://doi.org/10.1080/1612197X.2021.1987961

Patterson, M. S., Heinrich, K. M., Prochnow, T., Graves-Boswell, T., & Spadine, M. N. (2020). Network analysis of the social environment relative to preference for and tolerance of exercise intensity in CrossFit gyms. *International Journal of Environmental Research and Public Health, 17*(22), Article 8370. https://doi.org/10.3390/ijerph17228370

Patterson, M. S., Spadine, M. N., Graves Boswell, T., Prochnow, T., Amo, C., Francis, A. N., … Heinrich, K. M. (2022b). Exercise in the treatment of addiction: A systematic literature review. *Health Education & Behavior, 49*(5), 801–819. https://doi.org/10.1177/10901981221090155

Perry, B. L., Pescosolido, B. A., & Borgatti, S. P. (2018). *Egocentric Network Analysis: Foundations, Methods, and Models (Structural Analysis in the Social Sciences)*. Cambridge University Press.

R Core Team. (2024). *R: A language and environment for statistical computing. [Computer software]*. R Foundation for Statistical Computing. https://www.R-project.org.

Robins, G., Snijders, T., Wang, P., Handcock, M., & Pattison, P. (2007). Recent developments in exponential random graph (p*) models for social networks. *Social Networks, 29*(2), 192–215. https://doi.org/10.1016/j.socnet.2006.08.003

Santini, Z. I., Jose, P. E., York Cornwell, E., Koyanagi, A., Nielsen, L., Hinrichsen, C., … Koushede, V. (2020). Social disconnectedness, perceived isolation, and symptoms of depression and anxiety among older Americans (NSHAP): A longitudinal mediation analysis. *The Lancet Public Health, 5*(1), e62–e70. https://doi.org/10.1016/S2468-2667(19)30230-0

Schulte, M. T., & Hser, Y.-I. (2013). Substance use and associated health conditions throughout the lifespan. *Public Health Reviews, 35*(2), Article 3. https://doi.org/10.1007/BF03391702

Scott, J. (2017). *Social network analysis* (4th ed.). SAGE Publications.

Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks, 32*(1), 44–60. https://doi.org/10.1016/j.socnet.2009.02.004

Substance Abuse and Mental Health Services (SAMHSA). (2014). Recovery (National and Regional Resources). Region VIII. https://www.samhsa.gov/sites/default/files/samhsa-recovery-5-6-14.pdf.

Substance Abuse and Mental Health Services Administration (SAMHSA). (2024). *Key substance use and mental health indicators in the United States: Results from the 2023 National Survey on Drug Use and Health (HHS Publication No. PEP24-07-021)*. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. https://www.samhsa.gov/data/sites/default/files/reports/rpt47095/National%20Report/National%20Report/2023-nsduh-annual-national.pdf.

Suka, M., Yamauchi, T., & Sugimori, H. (2016). Help-seeking intentions for early signs of mental illness and their associated factors: Comparison across four kinds of health problems. *BMC Public Health, 16*(1), Article 301. https://doi.org/10.1186/s12889-016-2998-9

Sussman, S., & Sussman, A. N. (2011). Considering the definition of addiction. *International Journal of Environmental Research and Public Health, 8*(10), 4025–4038. https://doi.org/10.3390/ijerph8104025

The Association for Addiction Professionals (NAADAC). (2024). Recovery definitions. https://www.naadac.org/recovery-definitions.

The Phoenix. (2024). The Phoenix. https://thephoenix.org/.

Tracy, K., & Wallace, S. (2016). Benefits of peer support groups in the treatment of addiction. *Substance Abuse and Rehabilitation, 7*, 143–154. https://doi.org/10.2147/SAR.S81535

Valente, T. W. (2010). *Social Networks and Health: Models, Methods, and Applications*. Oxford University Press.

Valente, T. W., & Davis, R. L. (1999). Accelerating the diffusion of innovations using opinion leaders. *The Annals of the American Academy of Political and Social Science, 566*(1), 55–67. https://doi.org/10.1177/000271629956600105