SOCIAL RECOVERY CAPITAL

AMONG WOMEN IN EARLY RECOVERY

by

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Social Recovery Capital

Among Women in Early Recovery

Abstract

by

MEREDITH WELLS FRANCIS

Women's personal social networks (PSNs) often contain members (alters) who simultaneously support and endanger their recovery from substance use disorders, necessitating a holistic approach in theory, analysis, and practice. Network structure and trauma may also affect women's ability to use PSNs to support recovery. This dissertation aimed to 1) model the theoretical concepts of women's PSNs in recovery; 2) identify typologies of social networks in women in early recovery using PSN characteristics known to influence recovery, 3) examine the relationship between trauma and typology membership, and 3) link typologies to sobriety outcomes over their first year after entering treatment.

I used a 3-step latent profile analysis to 1) identify PSN typologies with 6 alter characteristics (sobriety, history of use with, sobriety support, treatment-related alters, isolates, and density), 2) relate Trauma Symptom Checklist (TSC-40) scores to typology membership, and 3) regress outcomes on typology membership in a sample of 377 low-income, racially-diverse women who were participating in residential or outpatient substance use disorder treatment at study entry.

I identified 3 typologies. Women in the Insulated Sobriety Support type (14.3%) had tightly-knit networks, more sober alters, and fewer treatment-related alters. Women in the Treatment-Related Sobriety Support type (49.3%) had looser-knit networks with

more sober and sobriety-supporting alters and alters they know from treatment. Women in the At-Risk type (36.3%) had more isolates, few sobriety-supporting alters, and more alters with whom they used. Women in the Treatment-Related Sobriety Support type were significantly more likely to maintain sobriety by 12 months (*B*=-0.81; OR=2.09, 95% CI [1.23-3.56]) than women in the At Risk type. Higher mean Trauma Symptom Checklist scores were positively related to membership in the At Risk type.

This dissertation expands our knowledge of the role that network structure plays in recovery among women, indicating that network isolates may represent key structural elements that can be leveraged to support recovery. This study also allows us to examine the patterns in recovery networks and trauma that support or hinder women's recovery from substance use disorders, which can provide a clinically-useful starting point for research on individualized, targeted, and trauma-responsive interventions for women in recovery.

Chapter 1: Introduction

About 7.75 million women out of 20.2 million American adults were diagnosed with a substance use disorder (SUD) as defined in the DSM 5 in 2014, and 1.33 million of them were actively involved in treatment (American Psychiatric Association, 2013; Center for Behavioral Health Statistics and Quality, 2015). The addiction crisis in our nation has had an impact on the policies and practices of our social service agencies (McClain, 2017), and having therapeutic approaches that can help heal the social disconnections caused by SUDs is increasingly important (Weir, 2017).

The social aspects of recovery from SUDs that are the focus of this dissertation have been identified as key targets for research and intervention by several national organizations influencing social work. The American Academy of Social Work and Social Welfare in their Grand Challenge Initiative on Eradicating Social Isolation identified that social isolation complicates recovery from chronic behavioral and health problems such as addiction, and that more research focused on how social networks impact health and well-being is needed (Lubben, Gironda, Sabbath, Kong, & Johnson, 2015). Likewise, the Recovery Support Strategic Initiative established by the Substance Abuse and Mental Health Services Administration has emphasized that a critical part of addiction recovery is to mobilize and strengthen the social resources available in the social networks of people in recovery, particularly in ways that are individualized (SAMHSA, 2015). Lastly, the National Institute on Alcohol Abuse and Alcoholism (2017, p. 51) has identified a need to focus on under-explored mechanisms of recovery from substance use disorders, and specifically those that impact the recovery efforts of vulnerable populations such as women.

The social work profession offers a uniquely holistic approach to meet this need for socially-focused research and practice in the addictions (McClain, 2017). The person-in-environment perspective is one of the central perspectives of social work, and this perspective aligns with the use of social network analysis in practice and research. Indeed, social network analysis has been identified as a valuable tool for research and practice within the social work perspective (Rice & Yoshioka-Maxwell, 2015; Tracy & Whittaker, 2015). This perspective allows for the examination in the dissertation of the social world of the individual in recovery for factors that promote or endanger recovery. However, it is necessary to first define "recovery."

Defining recovery.

The first 12 months of recovery from SUDs after ceasing use are critical, as approximately 40%-60% of people in recovery experience relapse during this time (McLellan, Lewis, O'Brien, & Kleber, 2000). Relapse, defined as the resumption of SUD symptoms after a period of abstinence (ASAM, 2013), is related to high costs to the individual and society, including increased risks for multiple health consequences for the individual (National Institute on Drug Abuse, n.d.), significant negative impact on their families (Coppello, Templeton, & Powell, 2010), and an annual United States cost of $417 billion dollars from property damage, loss of productivity, healthcare costs, and criminal justice costs related to substance use (Centers for Disease Control and Prevention, 2014; National Drug Intelligence Center, 2011).

However, substance use disorders are defined by the National Institute on Drug Abuse (2014) as chronic conditions in which relapse is a part of the recovery process and not an end point. This suggests that recovery can be conceptualized as a longitudinal process that evolves over the first 12-36 months after ceasing substance use (Laudet & White, 2008; 2010). This study focuses on the critical first year of recovery, and, based in the work of Laudet and White (2008), posits that there will be changes that occur over that time period.

Women as a special population for recovery.

Women have been identified as a special population with increased potential for problems with recovery from SUDs due to the differential impact of societal- and relationship-level stressors on their recovery as compared to men (Center for Substance Abuse Treatment, 2009; WHO, 2000). Compared to men, women experience more traumatic events, economic stress, poverty, and enforcement of traditional gender norms than men do (DeNavas-Walt & Proctor, 2015, Ouimette & Read, 2014; United States Government Accountability Office, 2011, WHO, 2000), and these present pervasive stressors which may influence the initiation of substance use and reduce resources for successful recovery. In addition, women are more influenced by their relationships than men are in all aspects of substance use, including being more likely to initiate use due to the influence of intimate partners, and escalating into higher-risk drug use behaviors because of involvement in significant relationships (Center for Substance Abuse Treatment, 2009, p. xix). These gender-specific stressors may place women in recovery within relationships that simultaneously support recovery and increase risk of relapse (Brown, Tracy, Jun, Park, & Min, 2015), or that enable substance use (Tracy, Munson, Peterson, & Floersch, 2010; Warren, Stein, & Grella, 2007; Wenzel, Tucker, Golinelli, Green, & Zhou, 2010; Falkin & Strauss, 2003). Because of this, this study focuses on identifying social factors that increase the likelihood of successful recovery for women in their first 12 months of recovery.

Egocentric social networks.

The first year of recovery is a time of changes in social relationships, with the person in recovery working to change their social network's composition from those who pose risks to their recovery to those who support recovery (Kelly, Stout, Greene, & Slaymaker, 2014), with these changes in network composition further reinforcing the recovery efforts of the recovering person (Best, et al., 2015).

The egocentric personal social network (PSN) is a mechanism for providing recovery-specific support to the person in recovery, and is comprised of all of the people with whom a focal individual interacts (Marsella & Snyder, 1981; Wasserman & Faust, 1994). The PSN's structure and the characteristics of the people in the network have an effect on the focal individual (Valente, 2010; Visser & Mirabile, 2004), and can influence their substance use or sobriety.

Specific characteristics of the social network members (alters) have been identified as important with respect to recovery from SUDs. In particular, alter characteristics such as their substance use or abstinence, their support for the focal person's recovery efforts, and their affiliation with formal or informal treatment have been previously shown to support or endanger recovery (Davey-Rothwell, Chander, Hester, & Latkin, 2011; Ellis, Bernichon, Yu, Roberts, & Herrell, 2004; Trulsson & Hedin, 2004). Likewise structural aspects of the network, such as network density—the ratio of actual relationship ties compared to the possible relationship ties within the network—and isolates—network members only connected to the focal individual—may provide a measure of the availability and accessibility of resources that support recovery within the network (Rice & Yoshioka-Maxwell, 2015; Tracy, et al., 2017).

This study will examine the aspects of social networks that have been shown to support or endanger the support of those in recovery from SUDs, including the aforementioned network alter characteristics and network structural characteristics.

Women's social networks in recovery.

Such a social network focus is important for women in recovery, as their social network resources and needs during recovery are different than those of men in recovery. As stated earlier, women are more likely than men to be influenced by friends in their social networks (Skaff, Finney, & Moos, 1999). Women in recovery tend to have relationships that simultaneously support recovery and increase risk of relapse, or that enable substance use (Brown, Tracy, Jun, Park, & Min, 2015; Falkin & Strauss, 2003; Tracy, Munson, Peterson, & Floersch, 2010; Warren, Stein, & Grella, 2007; Wenzel, Tucker, Golinelli, Green, & Zhou, 2010). Using the personal social network of the woman in recovery as the primary focus allows for a person-centered, individualized, holistic examination of the overlapping factors that support or endanger her recovery.

Trauma.

Trauma is an important contextual factor for the experience of women in recovery from SUDs, and one that has an impact on multiple areas of their lives, including their relationships. Women in treatment for substance use disorders also report experiencing significantly more traumatic events and are diagnosed with PTSD at a higher rate than men (Newmann & Sallmann, 2004; Ouimette & Read, 2014; Velez, et al., 2006). Estimates of the lifetime trauma rates for women with substance use disorders range from 55% to 75-85%, with some estimates showing up to 99%; women with SUDs also are diagnosed with Post-traumatic Stress Disorder more than twice as often as men, with rates of co-occurrence of these disorders up to 59% (Najavits, Weiss, & Shaw, 1997). The experiences of trauma and traumatic symptomatology that are so common among women in recovery can lead them to remain in relationships that are recovery-endangering because the experience of repeated traumas changes their belief in their ability to escape a problematic relationship (Gutierres & Van Puymbroeck, 2006). Likewise, experiences of trauma can decrease women's trust of others (Sun, 2007) and ability to form recovery-supportive attachments (Bollerud, 1990; Min, Tracy & Park, 2014).

Typologies of recovery.

Within an individual's personal social network, who is in the network, the characteristics of network alters, and the structure of the network are all interrelated; artificially separating these elements may not provide an accurate representation of the network. For example, having a higher network density can be beneficial to recovery if the network has many abstinent alters (Tracy et al., 2016), but harms recovery if the network contains mostly substance users (Latkin et al., 1995). Likewise, network alters who use substances are typically considered to be threats to recovery (e.g. Ellis, Bernichon, Yu, Roberts, & Herrell, 2004), but engagement in peer support groups such as 12-step organizations is linked to better recovery outcomes despite the fact that members of such groups may or may not be currently sober (Laudet & White, 2008). Rather than examining the relationships between the various aspects of a recovery network individually, it may be more empirically efficient and useful to examine them holistically to identify typologies of recovery networks (Collins & Lanza, 2010). This holistic approach is also supported in the theoretical literature on recovery, particularly literature on recovery capital, which states that it is the sum total of all of the individual strengths and weaknesses that indicates a person's potential for recovery, and that examining them individually or piecemeal may be less helpful than examining them in their entirety (Cloud & Granfield, 2008).

There are multiple paths to recovery (White & Cloud, 2008), and it stands to reason that varying combinations of network characteristics may all lead to successful recovery for women. However, while we know how many of the individual characteristics of a woman's PSN influence recovery outcomes, we do not know how these characteristics combine into recovery profiles or typologies. Being able to identify typologies of individual-level characteristics among women in recovery allows for more precise targeting of interventions in treatment for their addictions (Lanza & Rhoades, 2013), and tailoring the treatment intervention to the needs that the individual woman has in their recovery network can improve her outcome (SAMHSA, 2004). In addition, because the network structure provides information about the availability and accessibility of resources for recovery within the network, identifying network typologies that include network structural variables may offer valuable and practical insight into what combinations of network structure and alter characteristics are most supportive of women's recovery efforts.

Typologies of egocentric social networks in relation to various risk and resilience outcomes have been found in other populations such as risk of mental health issues in older LGBT adults, profiles of caregiver support, risk of sexually-transmitted infection for inner-city youth, and risk of misconduct among incarcerated youth offenders (Hopfer, Tan, & Wylie, 2014; Kim, Fredriksen-Goldsen, Bryan, & Muraco, 2017; Mitchell & Knowlton, 2012; Reid, 2017). However, no such typologies of social networks have been identified for women in recovery to this author's knowledge, and only one study examining social network typologies (Reid, 2017) incorporated network structural variables. This results in a gap in our knowledge of social networks in relation to a woman's recovery.

Aims.

In addition to identifying ways to more accurately model the theoretical concepts of women's social networks in recovery, this dissertation aims to fill this gap by using PSN characteristics known to influence recovery to 1) identify and describe typologies of social networks in women in early recovery, 2) examine the relationship between trauma and recovery typology membership, and 3) link these typologies to sobriety outcomes over the course of their first year of recovery.

In Chapter 2, Empirical and Theoretical Literature Review, I strategically review the empirical literature from which these research questions were derived using the literature search strategy presented at the beginning of the chapter. I also review and critique two relevant theories, the Transactional Model of Stress and Coping and Recovery Capital, as well as Kelly and Hoeppner's (2015) theoretical work that combines these two models. Finally, I articulate a theoretical model that expands upon this combined model in ways that more fully describe women's social networks in recovery, and present research questions and hypotheses that are derived from the empirical and theoretical literature.

In Chapter 3, Methods, I review the sample and the various measures used to operationalize the concepts being tested. I also review my plan for using latent profile analysis as an application of the theoretical model, with the results presented in Chapter 4.

In Chapter 5, Discussion, I integrate the theoretical conceptualizations and results presented in the previous chapters. I also explore the strengths and limitations of the study and potential avenues for future research. Finally, I explore the clinical, theoretical, and research implications of this dissertation research.

Chapter 2: Empirical and Theoretical Literature Review

This chapter is divided into three parts. The first part examines the empirical literature regarding personal social networks and women's recovery from substance use disorders. Using this literature as a base, the second section reviews two theories applicable to this population, The Transactional Theory of Stress and Coping (Lazarus & Folkman, 1984) and Recovery Capital (White & Cloud, 2008), as well as a proposed expansion of Kelly and Hoeppner's (2015) model which combines these two theories. Finally, a synthesis of the empirical and theoretical literature is presented along with three research questions that form the focus of this dissertation.

Empirical Literature.

Social Network Terminology.

This examination uses personal social network variables in relation to sobriety outcomes. The study of social networks focuses on alter composition and characteristics as well as the overall structure and organization of the network (Valente, 2010). Personal social networks, or egocentric social networks, are mechanisms for providing recovery-specific support to the person in recovery and are defined as all of the people with whom an individual interacts (Marsella & Snyder, 1981; Wasserman & Faust, 1994). In this dissertation, I use social network terminology that identifies the individual (ego) as the "participant" and all other network members as "alters."

Literature Review Criteria.

This literature review focused on studies that examined the effect of social network characteristics and network structure at treatment entry on substance use or abstinence outcomes. Studies focused on egocentric or personal social networks were included, but other types of social networks, including whole-network approaches that examine the relationships between a large set of individuals without selecting a primary focal individual (Valente, 2010), were excluded. I used broad search criteria to explore the full context of alter characteristics that impact recovery (e.g. personal social network, personal social network structure, egocentric network, specific network characteristic and structural terms, etc.). Studies included in the latent class/profile analysis review needed to focus on substance use and to use social network variables (alter characteristics and/or structure) as the indicators of the latent variable. Studies that focus on women are noted; all other studies discussed focused on a general population.

The review of the empirical and theoretical literature identified seven aspects of social networks that were shown to impact recovery outcomes. Alter characteristics identified were the substance use or abstinence of the alter, whether the participant used substances with the alter, whether the alter supported the participant's substance use or abstinence, and the alter's involvement with treatment. Network structural aspects identified were network density (the percentage of existing network ties out of all potential ties), isolates (alters only connected to the participant), and the size of the network. Because the participants in this study were all required to describe the characteristics of exactly 25 network members, there was no variation in network size in the sample, and this element was not examined for this study (for an explanation of the social network data collection method, see "Latent Profile Measures" in Chapter 3).

Network member substance use or abstinence.

Women who have social networks with higher numbers of people who are abstinent may be more able to maintain abstinence during early recovery. In general, having a higher percentage of abstainers or recovering network members was related to a significantly higher percentage of days abstinent and a lower monthly volume of alcohol use over the course of the three years following treatment entry (Zywiak, Longabaugh, & Wirtz, 2002). The converse is also true: Having substance users in the network can increase relapse risk for cocaine by a factor of 3 and for alcohol by a factor of 2.5 by 12 months after treatment entry (Broome, Simpson, & Joe, 2002). For women, having more drinkers in their network was related to having a higher percentage of drinking days (Manuel, McCrady, Epstein, Cook, & Tonigan, 2007). In particular, women who continued to have contact with people with whom they used substances had more problems with recovery: Women with low incomes who drank 6 or more drinks at a time at least once weekly, had 1.71 times the odds of having social networks composed of people they drank with (Davey-Rothwell, Chander, Hester, & Latkin, 2011).

Support for recovery.

Abstinent network members and support for recovery often go hand-in-hand. Having support specifically for their recovery from network alters can significantly improve a person's ability to maintain their sobriety during early recovery, and is related to having a lower percentage of drinking days, and fewer drinks per drinking day during the first year of recovery (Manuel et al., 2007), and nearly half the odds of using cocaine by 12 months (Broome et al., 2002). On the flip side, having a network that supports drinking was related to having fewer days abstinent, drinking a higher volume of alcohol per month, and having more drinks at one time, but only for the first 9 months after treatment entry (Zywiak et al., 2002).

Just perceiving your network as being supportive of recovery is associated with higher commitment to abstinence at the end of treatment for people in intensive outpatient treatment (Laudet & Stanick, 2010). Specifically for women in recovery from alcohol use disorders, having more alters in their network who are supportive of their recovery and who encourage them to participate in sober leisure activities significantly lowers the odds of heavy drinking (Davey-Rothwell et al., 2011).

Treatment-related alters.

Relationships with peers and professionals that women form through participation in treatment or peer support groups can be key sources of recovery support. Women who have just stopped using substances describe going through a period of struggling to regain control over their relationships, including learning to set limits with people in their networks (Rivaux, Sohn, Armour, & Bell, 2008). Friendships with others in recovery may provide a safe space in which women can practice these relationship skills (Trulsson et al., 2004).

Having a social network with a diversity of types of relationships including mentors or professional helpers is associated with increased social capital for women in low-income, low-resource settings like those encountered by many women in recovery, and may provide them with the needed resources to balance out threats to their success (Domínguez & Watkins, 2003). Not having treatment-related support for recovery is related to increased relapse risk. Compared to those reporting having support for abstinence from treatment-related alters, those reporting no support for abstinence were significantly more likely to report using alcohol in the past 90 days 1 year after entering treatment (Bond, Kaskutas, & Weisner, 2003). Similarly, women with low incomes who drank 6 or more drinks at a time at least once weekly had significantly fewer treatment-related alters in their networks (Davey-Rothwell et al., 2011).

Network structure.

Network density is calculated by comparing the number of existing ties within the network compared with the total number of possible ties, and it theoretically represents the availability, interconnectedness and flow of resources in the network. The level of density in a woman's network during recovery can be an indicator of the network's potential for informational flow and reinforcement of behaviors or beliefs, with higher levels of density being more reinforcing (Rice & Yoshioka-Maxwell, 2015). Isolates are network members who appear to be connected to the participant but not to any of the other network members. Theoretically, isolates within a recovery network may represent bridges or liaisons to novel resources that could support recovery (Granovetter, 1973; Valente, Gallaher, & Mouttapa, 2004). However, they can also represent isolated connections to substance users.

Few studies examining social networks and addictions to date have explored the role of network structure in adult recovery from SUDs. This technique has primarily been employed in public health applications, such as determining how information about risk-reduction for substance use flows through user networks (e.g. Wagner et al., 2013). Two older studies by Latkin and colleagues (1995) and by El-Bassel, Chen, and Cooper (1998), examined the role of network density on substance use outcomes. In the first study, higher network density was associated with a higher likelihood of injecting drugs, and this was theorized to be due to having networks in which the drug users are more enmeshed and more difficult to avoid (Latkin et al., 1995). The second study examined how network structure influenced the type and nature of social support that inner-city women on methadone maintenance received. They found that the majority of the women reported having high-density social networks with extremely close ties to alters, which was associated with greater likelihood of alters giving them financial support, but not emotional or recovery support (El-Bassel et al., 1998). Only one study has examined network isolates in relation to recovery. They found that having isolates in the network at 6 months after treatment entry also decreased the odds of using substances by 12 months for women, but only if those isolates are sober (Tracy et al., 2016).

Covariates impacting women's social networks in recovery.

The following individual-level elements affecting recovery are discussed here as potential covariates for the social aspects of recovery identified previously. While these elements are not aspects of a woman's social network, they all have the potential to affect her social network characteristics and structure, and, ultimately, her recovery prospects.

Trauma. Experiencing traumatic events and the subsequent traumatic symptomatology can constitute a pervasive stressor for women and impact their ability to create and utilize recovery-supportive PSNs. Women in recovery who have experienced trauma have been found to have decreased ability to trust (Sun, 2007), and may experience difficulty forming close social attachments that are recovery-supportive (Bollerud, 1990; Min, Tracy & Park, 2014). Often, women in recovery were introduced to substance use by significant others and remain in relationships with these intimate partners despite their continued substance use, and these relationships often are sources of past or present trauma (Ellis, Bernichon, Yu, Roberts, & Herrell, 2004; Grella, 2008). As Gutierres and Van Puymbroek (2006) showed in their qualitative work, women exposed to trauma can develop a lifetime cycle of feelings of low self-worth, helplessness, and powerlessness leading them to have a faulty appraisal of their own coping resources, which results in the use of maladaptive coping strategies such as substance use, ultimately increasing their risk of being in re-traumatizing situations. This iterative cycle of trauma and substance use may have implications both for the type of social network that a woman in recovery starts out with, as well as her ability to create a network that is recovery supportive during her first year after entering treatment. Compared to those who have not experienced trauma, women who have experienced trauma have increased difficulty managing interpersonal relationships effectively (Cloitre, Miranda, Stovall-McClough, & Han, 2005). They may have a harder time cutting ties with substance-using network members (Sun, 2007), leading them to have PSNs that are less recovery supportive.

Co-occurring mental health and substance use disorders. Co-occurring mental health and substance use disorders are linked with poorer recovery outcomes for women. For women, having co-occurring mental health and substance use disorders is associated with poorer treatment outcomes, including relapse, shorter retention in substance abuse treatment, and decreased abstinence self-efficacy (Conners, Grant, Crone, & Whiteside-Mansell, 2006; Greenfield, Venner, Kelly, Slaymaker, & Bryan, 2012).

Co-occurring disorders also negatively affect women's social networks. Women with co-occurring disorders tend to have more difficulty in accessing and using recovery supports (Biegel & Tracy, 2006) and experience less reciprocity within their relationships (Tracy & Johnson, 2007) than those who have only a substance use disorder.

Treatment modality. There are several modalities of treatment typically used for SUDs, including residential treatment, in which the person in recovery lives in a treatment facility for a period of time, and outpatient treatment, in which the person in recovery lives independently and attends treatment sessions at an outpatient facility. Participation in these different treatment modalities may affect both recovery outcomes and social networks for women.

Compared to women in outpatient treatment, women in residential treatment have been found to have greater numbers of substance users in their social networks (Kim et al. 2015; Min, et al, 2013). Women in residential treatment also have been found to have fewer people providing support in their social networks (Kim, et al., 2015), and fewer people from treatment programs or peer-led recovery programs in their networks compared to women in outpatient treatment (Min, et al., 2013). Women in residential treatment also tend to experience relapse of substance use more frequently following treatment than do those in outpatient programs, which may be related to their having a greater severity of SUD than those in outpatient treatment (Harpaz-Rotem, Rosenheck, & Desai, 2011).

Recovery Network Typologies.

From the review of emprical literature review above, we can see that women with networks composed of alters who are sober, who support, or who are involved in treatment are more likely to maintain abstinence after entering treatment, but it is unclear how all of these alter characteristics interrelate. Network density and the presence of isolates also are important for women‘s recovery, but whether they support abstinence appears to depend on the network alter characteristics. Thus, it is necessary to use an approach that examines the collective impact of both alter characteristics and network structure on recovery outcomes. Such an approach is latent variable analysis.

Typology-Based Analysis.

Latent class and latent profile analyses (LCA, LPA) use a person-centered approach that assumes an underlying heterogeneity of typologies that can be determined by identifying clusters of individuals with similar response patterns in the indicator variables examined, with LCA using categorical indicators and LPA using continuous and categorical indicators(Collins & Lanza, 2010). Several studies have used this methodology to identify baseline typologies of social networks, and these studies provide a framework for using social network data in the identification of latent typologies.

Three studies used LCA and one study used LPA to relate social network typologies at treatment entry or baseline to substance use outcomes. Bohnert, German, Knowlton, and Latkin (2010) used LCA based on dichotomization of count-type social network inventory data (Barrera & Gottlieb, 1981) to identify five patterns of social networks providing varying levels of social support in 1453 inner-city adults (Little/No Support, Low/Moderate Support, High Support, Socialization Support, and Financial Support). Those who had little or no support of any type from their social network members were more likely to have used substances within the past 6 months and to have friends who also used. Buckman, Bates, and Cisler (2007) focused on the relationship between a person's level of cognitive impairment at treatment entry and their level of abstinence support from their network. They identified three typologies of social support for abstinence (Frequent Positive, Limited Positive, and Negative) among 1726 people in outpatient or aftercare treatment for Alcohol Use Disorder using LCA based on created dichotomized social network variables representing patterns of alters' interactions with the participant, support for abstinence, and substance use collected using the Important

People and Activities instrument (Clifford & Longabaugh, 1991). They found that those with higher levels of abstinence support and greater cognitive impairment had the highest improvement in drinking outcomes, indicating that support for abstinence may disproportionately influence those with cognitive impairment. Finally, Hopfer, Tan, and Wylie (2014) used dichotomized data of substance-related social network interactions in LCA to identify latent risk profiles in a sample of 600 inner-city youth and young adults. Four profiles (Low Risk, Solitary Use, Social—Non-injection, and Social—All Substances) were predicted by selected individual sociodemographic (age group, housing situation, etc.) and infection status covariates such that those with higher risk of infection were more likely to use multiple substances with others in their social network.

Only one study (Reid, 2017) included network structural measures (size, density). This study used LPA with continuous proportional variables of network characteristics to identify social network typologies in relation to risk outcomes. While this study does not focus directly on substance use outcomes, it is of particular interest to this proposed study for its use of continuous variables and structural measures. They found three typologies of friendship networks among 144 male incarcerated youth offenders and then determined how membership in the identified network typologies related to individual-level risk factors that affect their rate of misconduct during incarceration using multiple group analysis. The study found that there was little difference in network size or density across these profiles, a finding that the author attributed to the limitations imposed by the institutional setting. In addition, there were some concerns that the sample size may have been too small to reliably distinguish network types.

Missing links.

Latent class and latent profile analyses have the potential to identify clinically-important patterns within the social networks of women in recovery. Social network data consists of counts of the various alter characteristics within a participant's egocentric social network. Many studies categorize this quasi-continuous data (e.g. Bohnert et al., 2010; Buckman et al., 2007; Hopfer et al., 2014), which reduces the information contained within the data, and risks changing the nature of individual differences such that all individuals above or below the cut point are equated regardless of their individual variation (MacCallum, Zhang, Preacher, & Rucker, 2002). While such categorization may make the identification of latent typologies simpler (Collins & Lanza, 2010), it holds the potential to miss clinically important relationships or variations in the data. Thus, there is a need for studies that examine non-categorized social network data.

Additionally, only one study (Reid, 2017) examined social network structure, and this study had multiple limitations on its ability to find meaningful classes in relation to structure. Finally, none of the studies identified that examined the latent social network typologies focused specifically on recovery, instead focusing on risk outcomes (Bohnert et al., 2010; Buckman et al., 2007; Hopfer et al., 2014; Reid, 2017).

Theoretical Concepts

This section examines several theoretical models that incorporate the concepts from the empirical literature presented in the previous section.

Egocentric social network analysis has been identified as a valuable tool for holistically modeling the person within their environment (Rice & Yoshioka-Maxwell, 2015; Tracy & Whittaker, 2015). Such a focus may provide better understanding of the mechanisms of recovery for vulnerable populations. Contextualizing the behavior of an individual with a substance use disorder within the social influences that surround them can make our theoretical understanding more comprehensive (Latkin, 2010). However, because of the complexity and the subsequent difficulty in conceptualizing and measuring social dimensions such as relationships or community influences, researchers often reduce these concepts to individual attributes such as the presence or absence of support rather than examine them holistically (Adams, 2016). This limitation in the way that we examine the social aspects of addiction has implications for both theoretical understanding of and practical interventions with women in recovery. Using social network analysis as a lens for theoretical discussion may be useful in addressing this need. Within addiction theory research, the organization, structure, and the characteristics of the people, or *alters*, in a focal person's network have an important effect on the attitudes, beliefs, and behaviors of the focal individual (Valente, 2010; Visser & Mirabile, 2004), and can influence the focal individual's substance use or sobriety.

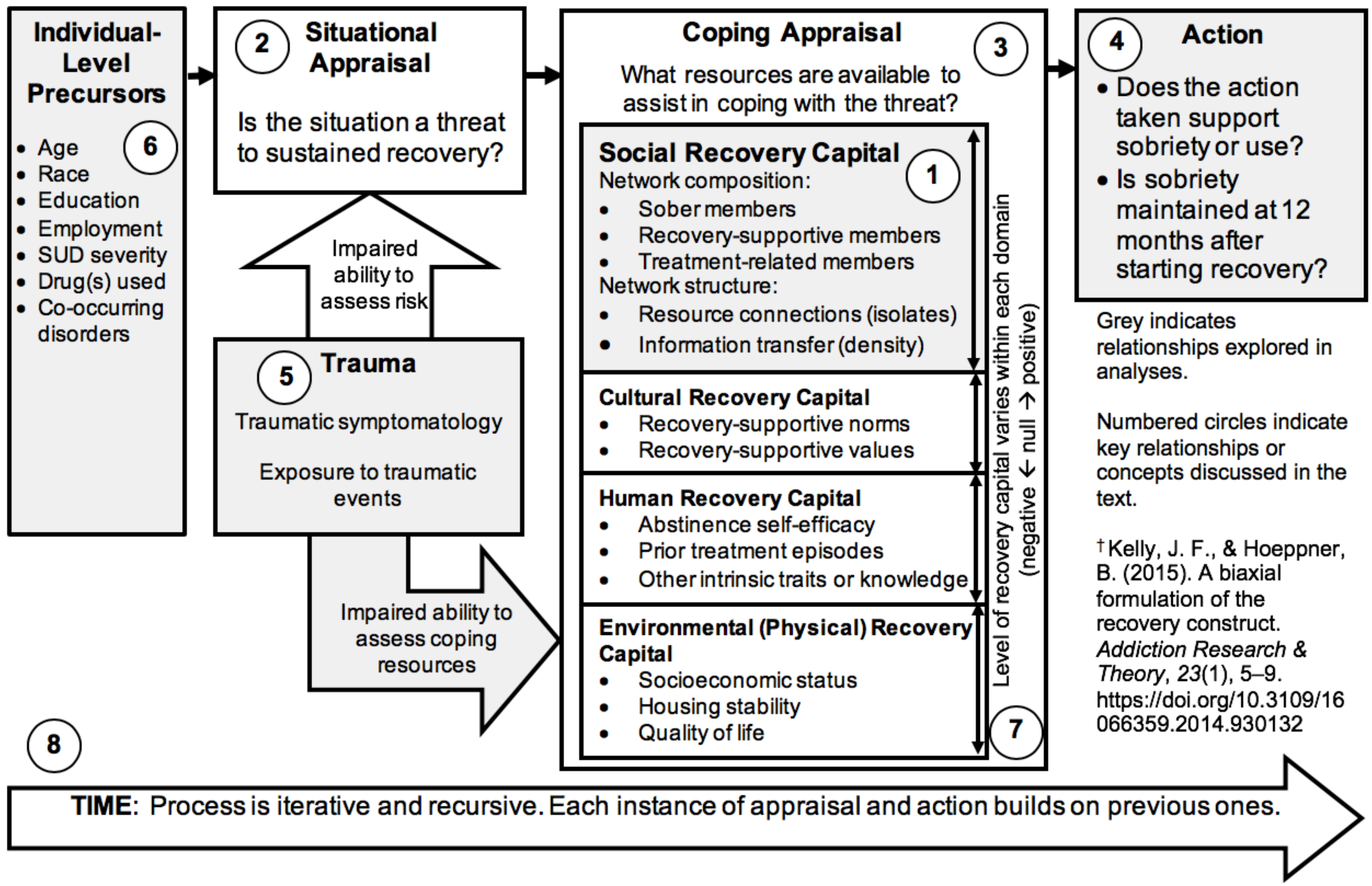
It should be noted that social network analysis is a tool or lens rather than a theoretical framework. However, the principles and methods of social network analysis can be incorporated into and enhance multiple theoretical approaches, as will be demonstrated here.

Current Conceptualizations of Addiction and Recovery.

Current theoretical explanations of addiction and recovery favor a complex etiology, combining biological, genetic, social, behavioral, and disease models (American Society of Addiction Medicine, 2011; National Institute on Drug Abuse, 2014), leading to the use of biopsychosocial theoretical models of addiction (e.g. Buchman, Skinner, &

Illes, 2010; Randle, Stroink, & Nelson, 2015). A person's recovery from substance use disorders also can be conceptualized longitudinally as a series of stages, extending over the first one to three years after initially ceasing use (Laudet & White, 2008; 2010). Thus, theoretical models used to study women's substance use disorder recovery need to be holistic, longitudinal, and provide a model of how individual processes within a social environment can impact recovery from addiction. Most relevant to the focus of this paper, previous researchers have highlighted the need for theoretical frameworks that are transactional or relational in nature and that use a social network approach in order to better understand how individual-level barriers, strengths, and stressors within the social environment function together to promote or hinder a person's recovery efforts (Neal & Christens, 2014; Neal & Neal, 2013). Two commonly-used theoretical frameworks that fit this need, Recovery Capital (a relational theoretical model) and the Transactional Model of Stress and Coping (a transactional theoretical model), are presented here, along with a biaxial formulation of recovery proposed by Kelly and Hoeppner (2015), which combines concepts from Recovery Capital and the Transactional Model of Stress and Coping. Finally, an expansion of Kelly and Hoeppner's model is presented that provides a more comprehensive model for working with women in recovery. This model is detailed in Figure 1. In-text discussions of concepts and relationships are linked to this model using the circled numbers in each box in the figure (e.g. ①). The shaded areas of Figure 1 represent the relationships that were tested in the dissertation analyses.

Figure 1: An expansion of Kelly and Hoeppner's (2015†) combined Recovery Capital and Stress-Coping model including trauma and social network variables



Recovery capital and social network resources.

Relational models of addiction recovery, such as Recovery Capital, focus on the types of relationships we have and the influence that those relationships have on us (Box 1). As noted previously, the compositional and structural focus of social network analysis fits neatly within this theoretical framework. In general, having a network composed of people who do not use substances and are supportive of recovery reduces risk of relapse for people in recovery (Bond et al., 2003; Davey-Rothwell et al., 2011; Day et al., 2013; Latkin et al., 1995; Manuel et al., 2007; Zywiak et al., 2002). Likewise, having substance users in the network increases risk of relapse significantly (Broome et al., 2002; Day et al., 2013; McDonald, Griffin, Kolodziej, Fitzmaurice, & Weiss, 2011).

The recovery capital model is drawn from the conceptualization of social capital as a practical resource that is derived from and generationally endowed by the person's institutional social networks and from those networks' historical contexts and larger environment (Bourdieu, 1998). This relational approach uses an examination of the individual's social network to identify both resources provided by alters within the network and the level of access to those resources inherent in the network's structure (Brunie, 2009). Both aspects of access are important. First, it is important to have people within the network with specific characteristics that provide access or connection, such as treatment professionals and peers in treatment. But access within a network is also determined based on structural aspects of the network. In this, loosely-tied networks with lower levels of density and the presence of network members that form bridges to new social groups or resources are both associated with higher levels of social capital (Brunie, 2009).

The conceptualization of the structural aspects of relational social capital, and particularly the role of bridging ties, was explored in detail in Granovetter's seminal article, "The Strength of Weak Ties" (1973). Granovetter identifies how network alters that are not strongly connected to others in the network, such as network isolates, may serve as informational bridges, allowing for more rapid diffusion of novel ideas to the focal individual. According to Granovetter, these "weakly-tied" alters are critical sources of information and links to new social groups during times of personal transition such as entering recovery (Granovetter, 1973). This concept was solidified and expanded on by Valente and others in study of how innovations in behavioral norms are diffused throughout communities using such weakly-tied alters, positing that alters who act as liaisons between separated groups may help norms spread more rapidly by sharing information and resources from one group to the next (e.g. Valente, Gallaher, & Mouttapa, 2004). Based on this, we may consider that the alters who appear to be isolates from the point of view of the focal individual's network are actually *liaisons* or *bridges* between the focal individual and an external network that has the potential to provide novel resources that their personal network cannot.

Within the social capital framework, both the available resources and how those resources flow within a network are posited to be defined by the norms of the social structure in which the network is embedded (Reimer, Lyons, Ferguson, & Polanco, 2008). For example, the norms that define what resources are available and how those resources are accessed will vary between family groups, mutual support groups, and agency-based relationships. What this means for women in recovery is that having a social network with ties to alters having a diversity of characteristics may indicate higher levels of social capital, in that this allows them to circumvent social structures that have norms that may conflict with their recovery goals and gain access to those that have norms that support their recovery.

Granfield and Cloud (2001) conceptualized Recovery Capital using a social capital paradigm to explore how differences in individual resources can impact that person's experiences in recovery. They found that people in recovery used their connections to social network members to maintain their stability (economic, job security, etc.), reinforce and reconnect with a recovery-supportive ideology (common beliefs about recovery, obligations, etc.), and to reinforce their sense of responsibility and relationship with others through maintenance of relationships that provide emotional support and demand reciprocity (Granfield & Cloud, 2001).

Cloud and Granfield (2008) later expanded the concept of recovery capital to include resources in the categories of environmental or physical capital (financial resources), and human capital (individual traits and knowledge), cultural (cultural norms and values), in addition to social capital. They defined social capital as concerning the individual's social network, including their informal support network of family, friends, and acquaintances, as well as formal support networks from engagement in recovery activities. They further theorized that recovery capital is best conceptualized as a continuous value that can be positive or negative (Cloud & Granfield, 2008). Positive recovery capital values would indicate that the sum of the aforementioned domains would balance out to provide support to the person in recovery, while negative recovery capital values would indicate that the sum of their domains was *un*supportive of recovery and may encourage relapse or maintenance of addictive behaviors. A recovery capital value of zero would indicate that the person's recovery capital domains balance out to provide recovery support and recovery threat in equal measure.

In addition, the theory of recovery capital incorporates the concept that capital for recovery can change over time, increasing or decreasing with the changes that occur in the person's internal processes, social world, and material world (Cloud & Granfield, 2008). This idea that recovery capital evolves over time was tested empirically by Laudet and White (2008), who found that there were changes in the level and domain of recovery capital over the first three years of recovery.

Women may experience lower levels of recovery capital than men do for multiple reasons. Some women described how family or friends encouraged or enabled substance use; others described how mutual support groups such as Alcoholics Anonymous often were inaccessible or non-supportive to them (Brown, Tracy, Jun, Park, & Min, 2015). In addition, the male-dominated, religion-oriented structure and language of mutual support groups may be re-traumatizing or depersonalizing for some women, limiting their engagement with this potential resource (Kornfield, n.d.; Straussner & Byrne, 2009; Vederhus, Laudet, Kristensen, & Clausen, 2010).

Within the recovery capital model, PTSD and other sequelae of traumatic experiences fall within the category of human capital, as this includes "acquired or inherited traits" such as mental health (Could & Granfield, 2008). However, cultural or historical traumas, such as racial discrimination, can negatively impact an individual's recovery capital, placing them at a higher risk for relapse (White, 2009), and these would fall within the cultural capital category.

While research specifically focused on recovery capital in relation to social networks or social support is in preliminary or exploratory stages with smaller samples and less sophisticated analyses, there is evidence of a link between a person's level of recovery capital and the composition of their social network. While many results are provisional, one study focusing on recovery capital found that perception of and identification with groups that use substances is correlated with lower social recovery capital (Mawson, Best, Beckwith, Dingle, & Lubman, 2015). Another found that those who have completed treatment and are in the recovery stage have higher recovery capital, fewer substance users in their personal social network, and more emotional or practical support from their network members as compared to those in active treatment (Best, McKitterick, Beswick, & Savic, 2015).

Only one study to this author's knowledge has attempted to use egocentric social network data to empirically test recovery capital. Panebianco, Gallupe, Carrington, and Colozzi (2016) attempted to link the social capital within individual personal social networks with recovery outcomes in Italian adults and found that maintenance of sobriety at 6 months after leaving treatment was related to having networks that had greater reciprocity, density, and closeness of ties, as well as having greater occupational diversity and higher socioeconomic status among alters. It should be noted that the study was small (n=88) and was cross-sectional in nature with insufficient power for multivariate analysis, so no causality could be established and specific profiles of risk could not be identified.

This limited empirical testing is the main critique of the recovery capital model. In addition, because it is based in a theoretical viewpoint that takes a macroscopic view of social problems, the recovery capital model has a much broader scale and scope than is typically used in examining social networks. This broad scope is helpful in looking at the sum total of the resources available within the network, and it allows for understanding how varying combinations of those resources, along with the potential for accessing those resources. However, the social recovery capital model does not explain the internal processes that determine how an individual interacts with these resources. What is also needed is an understanding of how the person assesses the resources available to them. For this, we turn to a transactional model.

The Transactional Model of Stress and Coping.

The Transactional Model of Stress and Coping (Lazarus & Folkman, 1984), often called the Stress-Coping Model, centers on the process or transaction that occurs between a person and their environment. In this model, the person performs a cognitive appraisal of the situation to determine if it contains a harm, threat, or challenge for them, as well as an appraisal of their own internal and external resources for coping (Boxes ②, ③; Lazarus & Folkman, 1984). Following the appraisals, the person takes an action intended to use these resources in order to restore their internal balance (Box ④). These appraisals combined with the actions which the person takes can be considered their coping process. This coping process is both recursive—the long-term coping process involves multiple repetitions of this situational process—and iterative, with each instance of appraisal and action building on the previous ones (Box ⑧). Over time, repeated experiences of appraising situations and coping resources and taking action change the elements contained within each step of the process. For example, using correctly-appraised coping resources to take an action that supports recovery may in turn change the appraisal of future situations as less recovery-threatening, and may increase perceived coping resources such as abstinence self-efficacy and knowledge of how to handle similar situations.

What is key here is that the appraisal and response actions are unique to each individual and situation and are based in that individual's perceptions of the situation. Thus, the influence and resources that a person perceives from their social network can alter their appraisal and coping processes. As noted previously, less dense networks with weaker ties can offer a wider variety of potential resources and alternative approaches to stressful situations (Granovetter, 1973). For example, having a connection to a peer in treatment could offer a woman in recovery an additional recovery-supportive coping resource to draw upon in a recovery-endangering situation.

Trauma affects the process of using the social network as a coping resource in the face of stressors in two problematic ways (Box ⑤). First, experiencing recurrent distressing or traumatic experiences can lead the person in recovery to have a faulty appraisals of the situation and coping resources, such as viewing situations as riskier or more threatening, having a negative appraisal of their ability to succeed in the face of stressors, or viewing their social network as an unreliable resource (Finkelhor & Browne, 1985; Lazarus, 1991). Second, some people who have been exposed to stressors develop "pathogenic coping actions," such as substance use or other health compromising behaviors, and related "self-deceptive thinking" that minimizes the risks inherent in these behaviors (Lazarus, 1991), which in turn can lead to appraisal of potentially risky situations such as those leading to relapse as less risky (Smith, Davis, & Fricker-Elhai, 2004). These converse reactions may occur in the same individual for different situations, and likely indicate an impaired ability to appraise risks and balance coping reactions appropriately to the situation (Herman, 1992). While Lazarus (1966) did not directly deal with traumatic stress, he conceptualized these types of balancing actions as part of the coping process and a sign of adaptive functioning in the face of a perceived threat.

The social network is typically viewed as a coping resource within the context of the Stress-Coping Model for people in recovery from substance use disorders (Bond et al., 2003; Dobkin, Civita, Paraherakis, & Gill, 2002; Thoits, 1995). As with relational models, many studies further break down the social network into specific characteristics of network members that provide coping resources or stressors, such as the network member's abstinence or substance use (e.g. Day et al., 2013), or support for recovery versus encouragement of substance use (e.g. Davey-Rothwell, Chander, Hester, & Latkin, 2011).

As can be seen, the shortcomings of the recovery capital model in examining the social networks of women in recovery are the strengths of the Stress-Coping Model in that this model primarily describes individual-level processes or transactions between the focal individual and the alters in their network. This micro-level focus allows for an examination of individual patterns of interaction that may be important clinically. However, this micro focus comes with some drawbacks when looking at the recovery networks of women.

Women in recovery may have relationships that can be simultaneously recovery-supportive and enabling of substance use, with network members providing needed supports, such as child care or money, that ultimately enable them to use (Tracy, Munson, Peterson, & Floersch, 2010). Similarly, women in recovery describe family members as supporting their recovery efforts, but acting in ways that increase their relapse risks due to family communication dysfunctions or lack of knowledge about recovery (Brown et al., 2015). Often these characteristics transcend the typical dichotomies of substance use versus abstinence or recovery supporting versus substance-use enabling, and do not adequately capture the complexity of the social networks of women in recovery making it difficult to fully separate out how an appraisal of stressors or resources might function for them.

Thus, it may be useful to use a combined Stress-Coping and Recovery Capital theoretical model to assess the stressors and resources contained within the social networks of people in recovery on a continuum as described in the Recovery Capital Model.

Kelly and Hoeppner's proposal: A combined model.

Kelly and Hoeppner (2015) postulated a combined conceptual model of the Recovery Capital and Stress-Coping models. They theorized that increasing lengths of time without substance use will correspond with increasing recovery capital and *vice versa*, and that the person's appraisal of and ability to cope with stressors will co-vary with this increasing recovery capital such that lower levels of recovery capital are related to decreased perception of coping ability and increased perception of situations as stressful or threatening, and higher levels of recovery capital are related to increased perception of coping ability and decreased perception of situations as stressful or threatening.

This model combines the best of both models described above, providing a more comprehensive view of the internal processes and external resources that women in recovery use than either model individually. In addition, the longitudinal nature of the combined model reflects current thinking regarding recovery as a longitudinal process extending over the first 12-36 months during active engagement in recovery work (Laudet & White, 2010, 2008).

This model lays a solid foundation for examining the process of addiction recovery over time. However, Kelly and Hoeppner's model (2015) focuses on recovery *in general*, and several expansions on the base model improves its ability to model women's specific recovery needs. Due to the need to look holistically at multiple domains of women's recovery, it is important to expand the model to show all domains of recovery capital, and to allow for a continuum with positive, null, or negative recovery capital within each domain (Box ⑦). Trauma also needs to be separated out to examine its independent effects on various points within the model rather than incorporating it as one of many other stressors in the stress-coping theoretical model (Box ⑤). Figure 1 shows how the base model can be expanded to more accurately model the specific needs of women in recovery.

Using this proposed framework, various aspects of a person's internal experience, such as the stressors they perceive, and their external world, such as the alter characteristics of their social network, could increase or decrease their recovery capital, thus altering their appraisal of the stressors or threats contained within a situation and their perceived ability to cope with those stressors. Trauma is shown as impacting both the situational appraisal and the coping appraisal, and the whole process is linked to recovery outcomes in both the individual decision instance and over the first 12 months of recovery.

Individual-level precursors (or covariates; Box ⑥) are shown as influencing the situational appraisal, but in reality impact multiple points within the model, and may be included within the coping appraisal. These covariates also have the potential to impact the woman's level of trauma exposure (e.g., Center for Substance Abuse Treatment, 2009; DeNavas-Walt & Proctor, 2015; Gutierres & Van Puymbroeck, 2006; World Health Organization, 2000).

This framework would allow us to separate out the specific aspects of a person's experience that either support coping ability or threaten recovery and place the sum total of all such aspects on a continuum in order to fully evaluate their potential for success in recovery, i.e. their negative, null, or positive recovery capital.

The benefits of using a combined theoretical framework become even more apparent when interpreting the impact of network structural variables on recovery. Using our combined theoretical lens, we can see that the level of network density affects the accessibility to stressors or coping resources, but whether that accessibility promotes or hinders recovery depends on the recovery capital represented by the network members. Likewise, having sober network isolates (those who are only connected to the focal person in the network) has been found to reduce likelihood of relapse for women (Tracy et al., 2016), and may represent attempts to increase recovery capital by adding recovery-supportive network members to an otherwise recovery-endangering network. In a qualitative study, women in recovery report attempting to mitigate the impact of recovery-endangering network members in an effort to maintain recovery (Tracy et al., 2010). Thus, theoretically, network isolates may also represent an attempt to cope with a potential stressor by limiting contact with a network member who endangers their recovery.

Synthesis of empirical and theoretical literature.

When we combine the presented theoretical model with our understanding of the empirical literature, we are able to see the strengths of this model. The holistic view of the social recovery capital of the elements of coping appraisal (Box ④) aligns with the holistically-focused methodology of latent variable analysis. Using this methodology, we can identify latent typologies of social recovery capital. These can model her social coping resources she would appraise when faced with a recovery-threatening situation (Box ②). Trauma (Box ⑤) can be modeled as affecting the coping appraisal by predicting how the woman perceives her social network as recovery-supportive or recovery endangering—in essence, which typology she fits within. Finally, typology membership can be related to the actions the woman takes following her coping appraisal, both in the immediate instance of action and in the accumulation of multiple instances of appraisal and action that make up her recovery experience during her first year after ceasing use. Based in this model and in the empirical literature, the following research questions and hypotheses are proposed.

Research questions and hypotheses.

Research question 1a: Are there latent typologies of social recovery capital within the social networks of women who have recently entered treatment for a substance use disorder?

Research question 1b: How do these identified typologies differ from each other in demographic and clinical characteristics?

Hypothesis 1a: The sample will separate into at least two latent typologies representing varying levels of social recovery capital as operationalized by the compositional and structural social network variables. It is expected that greater numbers of treatment-related peers and professionals, sober alters, and recovery-supportive alters, and fewer alters with whom the focal person used will represent greater social recovery capital. It is expected that the level of the structural variables, density and isolates, will further separate and define the classes.

Hypothesis 1b: The classes will differ with regard to demographic and clinical characteristics.

Research question 2: How does traumatic symptomatology affect latent typology membership at one week after entry into treatment for substance use disorders?

Hypothesis 2: Higher levels of traumatic symptomatology will increase the probability of membership in latent classes with lower levels of social recovery capital at one week after treatment entry, and vice versa.

Research question 3: How is membership in the identified latent typologies at one week after entering treatment associated with a woman's ability to maintain sobriety over the first 12 months after entering treatment, after controlling for demographic and clinical characteristics?

Hypothesis 3: Compared to women in latent classes representing lower levels of social recovery capital, women in latent classes representing higher levels of social recovery capital will have greater likelihood of achieving sustained recovery as operationalized as lack of substance use at 6 and 12 months after entry into treatment, after controlling for demographic and clinical characteristics.

Chapter 3: Methods

This study involved the identification of network typologies with 6 social network variables using the three-step latent profile analysis (LPA) approach described in Asparouhov and Muthén (2014b). These typologies represented the various types of social networks found in the sample at one week after entry into substance use disorder treatment, and were related to the woman's level of traumatic symptoms as a predictive covariate to the latent profile variable and to the woman's ability to maintain sobriety over the 12 months following treatment entry as a distal outcome.

This section will review the characteristics of the study sample, the social network variables used in the LPA, the trauma covariate, the abstinence outcome, the demographic and clinical covariates, and the analysis plan for the study.

Parent Study

This study used de-identified data from the prospective, longitudinal study, "The Role of Personal Networks in Post Treatment Functioning" (R01 DA 022 994 01A2, Dr. Elizabeth M. Tracy, Principal Investigator). The parent study collected data from women enrolled in residential or intensive outpatient substance use disorder treatment for one week at study entry (T1), as well as at 1 month (T2), 6 months (T3) and 12 months (T4) after study entry. Types of data collected included social network information, substance use, psychological symptomatology and functioning, quality of life, and demographic data. Women were considered for inclusion in the parent study if they were 18 years of age or older, had been enrolled for one continuous week in one of three treatment programs for substance use disorders, had a DSM-IV diagnosis of substance dependence (American Psychiatric Association, 1994), and were not diagnosed with or taking medication for a major thought disorder such as schizophrenia. The study data were collected between October, 2009, and May, 2012. Compensation for participation at each time point was a $35 gift card to a local store and reimbursement of travel costs. The parent study was approved by the Institutional Review Board of Case Western University.

Participants

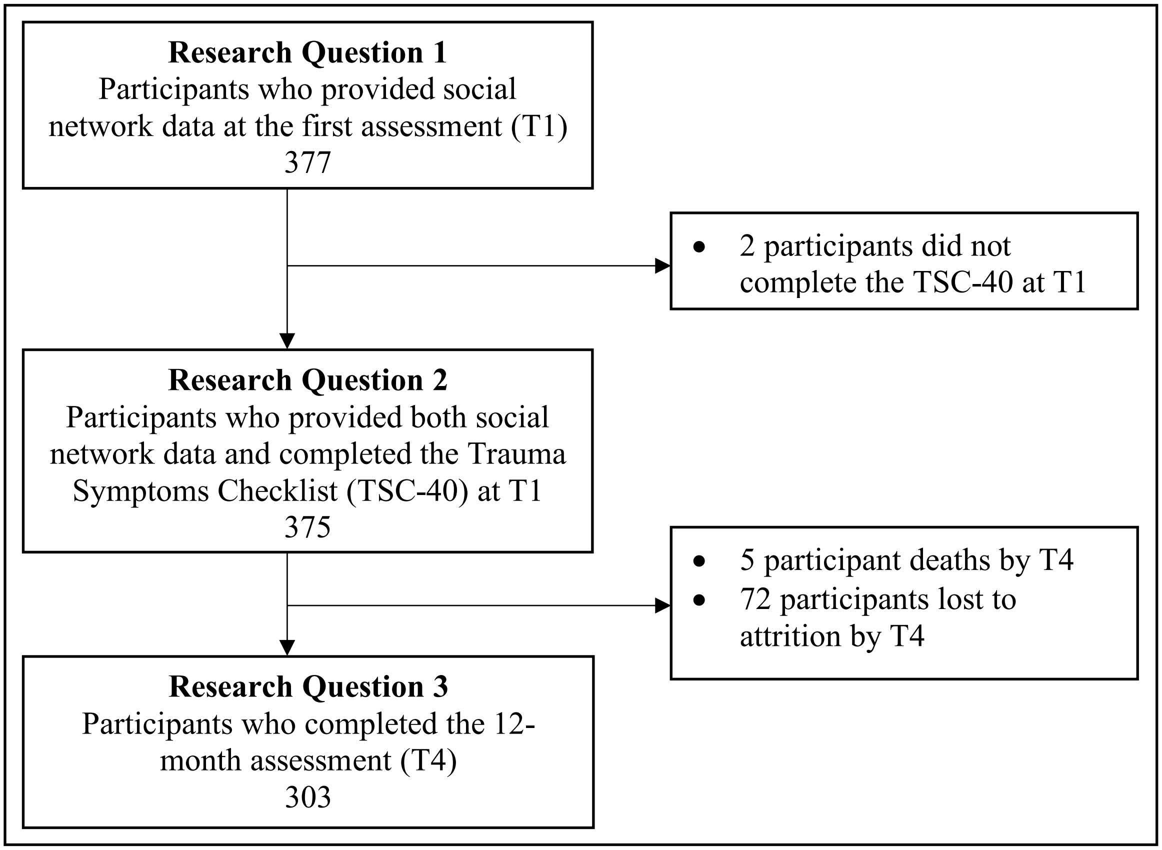
The sample for this current study was comprised of the 377 women (the full parent study sample) who provided social network data at one week after treatment intake (T1). Complete demographic and clinical characteristics for this sample are presented in Chapter 4: Results.

Missing data

Per inclusion criteria, there were no missing data on the social network variables used in establishing the LPA model. Missing data on the TSC-40 covariate used to predict class membership resulted in a sample size of N=375 for this analysis. Missing data on the outcome variable resulted in a sample size of N=303 for regression analysis. An examination of the remaining cases using multiple imputation for pattern analysis indicated that any cases missing demographic or clinical data were missing at random. Please see Figure 2 for the sample derivation flow chart for each research question.

Figure 2.

Sample derivation flow chart



Measures.

Latent profile measures. Egocentric social network data were collected at T1, T2, T3, and T4 with a computer-assisted interview using Egonet software (McCarty, 2002; McCarty et al., 2007). This study incorporated social network data from T1. Social network data were obtained by asking the respondent to 1) identify 25 network members (alters) with whom they had contact in the previous 6 months; 2) provide information about various characteristics of those alters (e.g. relationship to the respondent, substance use or sobriety, supportiveness, etc.); and 3) how each unique pair of alters was connected to each other. Social network variables used in this analysis are: Alter sobriety;

substance use with the alter; treatment-related alters (including treatment providers, peers in treatment, and peers in support groups); sobriety support; isolates; and network density. Operationalization of these variables is shown in Table 1, and descriptive statistics for the LPA variables are provided in Table 2. As can be seen in Table 2, the women in the sample reported having networks with an average of 17 sober alters (*m* = 16.56, *sd* = 4.90) and 20 alters who supported their sobriety efforts (*m* = 19.62, *sd* = 4.94). The women reported an average of about 6 alters they had previously used with (*m* = 6.26, *sd* = 4.61) and an average of 3 or 4 alters involved in treatment (*m* = 3.54, *sd* = 4.19). Network density was on average about 25%, and the women reported an average of 5 isolates in their networks (*m* = 4.98, *sd* = 5.43).

Table 1.
Variable descriptions for latent profile analysis

Variable	Operationalization
Sobriety support	The number (0-25) of alters for whom the focal individual responded “Almost Always” for “Would this person give you support to stay clean?”
Alter sobriety	The number (0-25) of alters for whom the focal individual answered no to “Does this person do alcohol or drugs?”
Alters “used with”	The number (0-25) of alters for whom the focal individual answered yes to “Is this person someone you used with?”
Treatment-related alters	The combined responses for two options on the question, “How do you know this person?” (“Professional helper” and “From treatment program or AA/NA”). Range: 0-50.
Isolates	The number (0-25) of alters identified as only having a network tie with the focal individual and not with any other alters.
Density	Network density is measured by dividing the number of observed ties between alters by the number of possible ties, with a range of 0-1.00.

Table 2.
Descriptive statistics of variables used in latent profile analysis (*N*=377)

Variable	*M*	Minimum	Maximum	*SD*
Alter sobriety	16.56	2	25	4.90
Alters "used with"	6.26	0	20	4.61
Treatment-related alters	3.54	0	22	4.19
Sobriety support	19.62	0	25	4.94
Isolates	4.98	0	25	5.43
Density	0.27	0.00	1.00	0.25

Trauma. The women's total score on the Trauma Symptom Checklist (TSC-40; Briere, 1996) was used as a covariate in the second step of the 3-step LCA process. The TSC-40 gives an indication of the level of traumatic symptomatology experienced by the participants, and is a continuous variable with a range of scores from 0 – 120 with higher scores on all items indicating increased frequency of traumatic symptoms. The TSC-40 has no clinical cutoffs and is designed for research purposes only. Previous studies have demonstrated the reliability of the TSC-40 total scale with a range of α=.89 to α=.91 (Briere, 1996). The TSC-40 has also been found to demonstrate construct and discriminant validity in victims of sexual abuse (Briere & Runtz, 1987; Elliott & Briere, 1992), and in a psychiatric inpatient sample (Zlotnick, Davidson, Shea, & Pearlstein, 1996). Chronbach's alpha for the 271 women who completed the TSC-40 in this sample was high, α=.93.

Sobriety outcome. The sobriety outcome was measured using a dichotomous yes / no question from the Individualized Assessment Profile (IAP; Flynn et al., 1995): "Have you used any substance once or more to get high or to feel better since the last interview?" Responses were reverse-coded such that positive responses indicated maintenance of sobriety. Sobriety outcomes over the first year after treatment entry were measured using the combined T3 (six month) and T4 (12 month) responses, with no reported use during the 12-month period coded as “sobriety.” The specific substances the respondents reported using prior to study entry are presented for descriptive purposes in Table 4 (p. 53).

Covariates. The following variables were used to describe the demographic and clinical characteristics of the sample, and considered as covariates in the final regression analysis of recovery network typology on sobriety outcomes. Only covariates that were strongly indicated by the literature to affect recovery networks and showed low indications of multicollinearity ($r<0.60$; Leech, Barrett, & Morgan, 2015) were included in this analysis due to the small sample size across the various network profiles. Data for all covariates were collected at one week after treatment intake (T1), unless otherwise specified.

Demographic characteristics were collected using the Computerized Diagnostic Interview Schedule (CDIS; Helzer et al., 1985; Robins, Helzer, Croughan, & Ratcliff, 1981). Variables were dichotomized for simplicity in the regression analyses; detailed categories can be seen in Table 4 (p. 53). The following demographic characteristics were used in analysis: Age in years, racial and ethnic groups (dichotomized into 0 = “Non-black”; 1 = “Black”), educational level (1 = “Elementary/Junior High”; 2 = “High School or Higher”), and income source (1 = “Welfare/Government. Assistance”; 2 = “Employed / Other”).

Clinical characteristics used were the respondents’ treatment modality (0 = “Residential”; 1 = “Outpatient”) as reported by the treatment programs to the study investigators, the presence of any psychiatric diagnoses as measured by the CDIS both in aggregate (dual disorder, Yes/No); the specific psychiatric diagnoses observed in the sample are presented for descriptive purposes in Table 4 (p. 53).

Analysis Plan

The analyses in this study were conducted in three stages using the three-step method described in Asparouhov and Muthén (2014b), who introduced a three-step methodology for conducting latent profile analyses in order to address the issue of inaccuracies in error estimation when using the identified latent typologies in regression analyses or covariate analyses. This method produces superior error estimation to other methods such as multiple pseudo-class draws or using the marginal distribution of the distal outcome variable (Asparouhov & Muthén, 2014b).

The three steps are as follows: 1) Identify the classes using only the LPA variables; 2) Identify the most likely class for each case using the posterior distribution and incorporating the classification uncertainty rate (i.e., error); 3) Create a latent profile indicator variable with fixed error rates derived from the classification uncertainty rates identified in step 2. This variable can then be used directly in analyses of covariates and distal outcomes with the identified latent typologies.

This method can be used to adequately address research questions 1 (identification of latent typologies) and 2 (trauma as a covariate). However, this method does not allow for the use of control variables when regressing the distal outcome, abstinence, on the latent typology variable, and this was identified as a necessary step for research question 3 (the effect of typology membership on distal sobriety outcomes). Clark and Muthén (2009) identify that using the most likely class membership in analyzing the relationship between class membership and distal outcomes is as effective in estimating the true value of class membership as other methods when the entropy values are ≥ .80. Based in this, the sample was divided by most likely typology probability as identified in the first step, and this was used in a regression analysis with control variables and the distal outcome to address the third research question.

Univariate, bivariate, and regression analyses that included control variables were conducted using SPSS, Version 24 (IBM Corp., 2016). Latent variable analyses were conducted using M*Plus*, Version 8 (Muthén & Muthén, 2017).

Preliminary univariate and bivariate analyses.

Bivariate correlations between the demographic or clinical variables and the sobriety outcome with significance of $p<.20$ indicated that these variables should be included in the regression model (Mickey & Greenland, 1989). Table 3 that shows four variables met this criterion: TSC-40 score ($r(304)=-.157$, $p=.006$), dual diagnosis ($r(303)=-.203$, $p<.001$), treatment type ($r(304)=.084$, $p=.144$), and income source ($r(291)=-.079$, $p=.181$); none of these variables correlated with each other above .396, indicating low likelihood of multicollinearity (Mickey & Greenland, 1989). All continuous variables included in the regression analyses showed normal distributions with skewness < |2.0| and kurtosis < |7.0| (Curran, West, & Finch, 1996). Latent profile analysis (LPA) does not assume univariate normality outside of the identified typologies; similarly, LPA indicators are considered dependent variables under the model, there is no need to examine the variables at the bivariate level for multicollinearity (Collins & Lanza, 2010).

Table 3.

Correlations between covariates and abstinence outcome

	1	2	3	4	5	6
1. Age (in years) (*N* = 377)						
2. Racial / ethnic group (*N* = 279)	.23*					
3. Education (*N* = 376)	.22*	-.15*				
4. Employment type (*N* = 360)	.05	.23*	-.17*			
5. Outpatient treatment (*N* = 377)	-.01	.04	-.07	.01		
6. Dual diagnosis (*N* = 376)	.14*	-.15*	.09	.03	-.02	
7. 12-month sobriety (*N* = 304)	.03	.05	.06	-.08	.08	-.20*

* $p < .20$

Research question 1a.

Research question 1a asked: Are there latent typologies of social recovery capital within the social networks of women who have recently entered treatment for a substance use disorder? This study addressed Research Question 1 using the three-step latent profile analysis method in M*Plus* (Asparouhov & Muthén, 2014c).

Latent Profile Analysis (LPA). LPA is a type of mixture modeling that uses observed, continuous variables, such as the percentages of social network members with a specific characteristic, to identify latent typologies that are mutually exclusive and exhaustive (Gibson, 1959; Tein, Coxe, & Cham, 2013). For the purposes of this study, the terms “latent profile” and “latent typology” are used interchangeably when describing the identified groupings of individuals based on the proposed social recovery capital latent variable.

LPA is considered a person-centered analysis rather than a variable-centered analysis (Gibson, 1959; Tein, Coxe, & Cham, 2013). This approach is useful for identifying individual-level patterns within multidimensional latent constructs, such as social recovery capital. This identification of individual-level patterns then allows for the creation of meaningful, homogenous subgroups of individuals with a particular response pattern (Muthén & Muthén, 2017). Assumptions for LPA, notation of parameters, model equations, standard parameter restraints, and how parameters are estimated can be found in Appendix A.

Model identification and selection. Of primary interest in LPA is whether and how well the latent variable separates into defined profiles or typologies. The *homogeneity* of the latent profile is the extent to which members of a latent profile can be expected to give the same observed response pattern (Collins & Lanza, 2010). Linked to this is the concept of latent class separation. The latent classes of a latent variable are considered to have high separation when there is high homogeneity and little overlap in the response patterns between classes. In other words, each latent class has a response pattern that is clearly characteristic of that class and clearly not characteristic of any other class (Collins & Lanza, 2010). The homogeneity and separation of the latent classes will be examined by plotting the overall mean scores for indicators within each profile linearly and comparing the graphs to determine if each profile shows a distinct and clear pattern separate from the other profiles (Collins & Lanza, 2010, pp. 59-63). Model separation will be assessed using the Mahalanobis distance (D), with D = .50 indicating small, $D = .80$ indicating intermediate, and $D \geq 1.20$ indicating large separation conditions (Gitta Lubke & Neale, 2006; Peugh & Fan, 2013).

While the number of potential latent profiles or typologies can be determined by theory or prior empirical testing, the number of typologies in this study was unknown. Thus, the identification of the number of typologies proceeded with testing for $k = 1$ profiles (i.e. testing the assumption that there are no distinct latent profiles), and increasing the number of profiles allowed in the model until there was a decline in fit statistics. The model with the best-fitting number of latent profiles was determined using a combination of model fit statistics, identification of the model and stability of the solution, and interpretability of the profiles. The detailed application of the steps comparing model fit results is presented in Chapter 4: Results.

Model identification in LPA requires $df \geq 1$ in order to obtain a ML solution. Models that are under-identified or unidentified will result in no clear ML solution, if unidentified, or a multimodal solution in which the true ML solution estimate is difficult to determine (Collins & Lanza, 2010). In order to reduce the likelihood of model selection based on local maxima, the number of random model start values was set at 100 and increased as needed to reach convergence (Berlin, Williams, & Parra, 2014; Collins & Lanza, 2010). The distribution of the log-likelihood (LL) values was examined to determine if there was a multimodal distribution. Additionally, the percentage of the model start values obtaining the same ML solution estimate was calculated, with ≥ 60% of start values identifying the same ML solution indicating adequate model selection (Collins & Lanza, 2010). There was a possibility that model identification would be unclear from the LL distribution, indicating that the model was under-identified or minimally identified. In this case, either removal of one or more poorly-performing indicators or imposing additional parameter restrictions was considered (Collins & Lanza, 2010).

In their simulation of identification and selection of latent classes using LPA, Tein, Coxe, and Cham (2013) identified that indicators with an inter-class distance (Cohen's *d*) $<.8$ did not reliably allow for correct identification of latent classes, and instead tended to bias class selection towards models with fewer classes. They recommended that LPA be run iteratively with indicators with small inter-class distances discarded.

The following model fit statistics were used to select the final model, and are reported in the results chapter. It should be noted that it is rare for all criteria to indicate the same solution as optimal, so all criteria were examined as a whole along with model identification and interpretability for final model selection (Collins & Lanza, 2010).

- Models with K and K - 1 profiles were compared using the **Lo-Mendell-Rubin likelihood ratio test** (LMR; Lo, Mendell, & Rubin, 2001), which uses weighted chi-square statistics to compare the two models with approximate sampling distributions. Significant p-values on the LMR test indicate that the model with the larger number of profiles should be selected.
- The **Akaike information criterion** (AIC) and **Bayesian information criterion** (BIC) are both fit statistics that impose a penalty on G^2 using different methods. Smaller values on these criteria indicate more optimal balances of model fit and parsimony, and the model with the minimum AIC or BIC is desired.

- As discussed previously, **entropy** is the weighted average of the individual posterior probabilities (range: 0 to 1), with higher values indicating better prediction of class membership (Collins & Lanza, 2010). Entropy values ≥ .80 indicate that study participants were correctly classified into latent profiles at least 90% of the time (G. Lubke & Muthen, 2007).

The **interpretability and practicality of the models** was also considered during model selection. The typologies identified by the various models must be interpretable and have practical clinical value (Collins & Lanza, 2010). In addition, models with a very small proportion of individuals in one class (i.e. < 10% of the sample) may not be practically useful in the further analyses (Collins & Lanza, 2010). However, such small classes may represent a clinically meaningful group for this population, and were examined and considered for inclusion.

The average latent class probabilities for most likely latent class membership by latent class are calculated following model selection, with values on the diagonal indicating the probability that you have classified an observation into the correct class (Asparouhov & Muthén, 2014a).

Comparison of typologies. The social network variables have a variety of ranges. For example, while most of the social network variables have a range of 0-25, treatment alters (0-50) and density (0-1) use a different scale. There is also no standard with which to compare the variables, meaning that there is no way to know whether a count of 5, for example, is a high or low value. Because of both of these reasons, this study converted the mean scores for the social network variables in each profile to *z*-scores so that the scores within the profiles could be compared to the overall study mean for each variable. This allowed for direct comparison of the social network variables between the profiles.

Research question 1b.

Research question 1b asked: How do these identified typologies differ from each other in demographic and clinical characteristics? As discussed previously, using the most likely class membership in analyses is sufficient when entropy values are ≥ .80 (Clark & Muthén, 2009). The sample was separated using the most likely class membership and the characteristics of the latent typologies, and *t*-tests and chi-squared tests were used to compare the identified latent typologies on the demographic and clinical characteristics. All continuous demographic and clinical variables showed normal distributions with skewness < |2.0| and kurtosis < |7.0| (Curran et al., 1996).

Research question 2.

Research question 2 asked: How does traumatic symptomatology affect latent typology membership at one week after entry into treatment for substance use disorders? This question examines the relationship between the level of trauma symptomatology (TSC-40 score) and the latent profile indicator variable for the identified typologies created in the 3-step LPA. The TSC-40 score is used as a covariate that predicts membership in the typologies. In M*Plus*, this is accomplished using the R3STEP macro that performs multinomial logistic regressions of the latent profile indicator variable on the TSC-40 score. Using this macro allows the classification error of the latent profile variable to be correctly estimated.

Research question 3.

The third research question asked: How is membership in the identified latent typologies at one week after entering treatment associated with a woman's ability to maintain sobriety over the first 12 months after entering treatment, after controlling for demographic and clinical characteristics? This study addressed research question 3 using a hierarchical logistic regression analysis that included the control variables identified in bivariate analyses as being correlated at $p<.20$ with the outcome variable: Dual diagnosis, treatment type, and income source. The TSC-40 mean score was excluded from this analysis despite meeting the criteria due to its inclusion as a covariate under research question 2, which examines the role of the latent profiles as a mediating variable between trauma symptoms and the outcome. None of these variables correlated with each other above .396, indicating low likelihood of multicollinearity (Allison, 1999). All continuous variables included in the regression analyses showed normal distributions with skewness $< |2.0|$ and kurtosis $< |7.0|$ (Curran et al., 1996). Latent profile analysis (LPA) does not assume univariate normality outside of the identified typologies; similarly, LPA indicators are considered dependent variables under the model, and there is no need to examine the variables at the bivariate level for multicollinearity (Collins & Lanza, 2010).

Once again, the sample was separated using the most likely class membership and the characteristics of the latent typologies for the regression of the distal outcome on the latent typologies, per Clark and Muthén (2009).

Regression analysis. The logistic regression analysis was conducted using hierarchical entry of the predictor variables on the abstinence outcome in two blocks. The first block included the two clinical covariates: treatment modality and dual diagnosis. The second block included the latent profile membership.

Model fit. Goodness-of-fit of the regression model was examined after entry of each block of predictor variables using Hosmer and Lemeshow's Chi-squared test, in which significance indicates poor model fit (King, 2008), and Nagelkerke's index, which is a measure of pseudo-R^2 with a maximum value of 1 and which adjusts for over-estimation of variance (Cohen, 2003). In addition, the usefulness of the model was indicated if the final model's classification accuracy rate, or the percent of cases correctly predicted by the equation for both conditions of the outcome variable is greater than or equal to than the proportional by-chance accuracy rate from the initial block (Schwab, 2007).

The assumptions of logistic regression are that there is a linear relationship between the variables, that there is no collinearity, and that there is independence of errors. As per Lomax and Hahs-Vaughn (2012) violation of these assumptions was determined as follows. Multicollinearity was determined by VIF values < 10 and tolerance values > .10. Linearity was assessed by adding an interaction term for each focal variable with its natural log to the regression model. Significance of the interaction term indicates violation of the linearity assumption. Interdependence of errors is indicated when plotted values for the standardized residuals against each independent variable are less than +/- 2.

Multivariate outliers were identified as those cases with residuals falling more than 3 standard deviations above or below the mean (King, 2008). Influential outliers was identified using values of Cook's Distance > 1.0, dfBeta values > 1, and leverage values > .50 (Lomax & Hahs-Vaughn, 2012).

Chapter 4: Results

Sample characteristics.

Complete demographic and clinical characteristics for the sample are presented in Table 4. At T1, the women in this sample had an average age of 36.5, were 59.4% African American, 72.5% were on public assistance, 58.0% had at least a high school degree, and 31.6% were in residential treatment. The mean Trauma Symptom Checklist (TSC-40) score was 44.70 out of a possible total score of 120, higher than means reported in previous studies (Briere, 1996; Cash Ghee, Johnson, & Burlew, 2010). On average, the women reported being dependent on an average of about two substances and up to 6 substances simultaneously (M = 1.81, sd = .86). Forty-seven percent of the women reported maintaining sobriety over the 12 months following treatment entry.

Table 4.

Demographic and clinical characteristics at study entry, one week after treatment intake

	n (%)	*M* (*SD*)
Age (in years) (*N* = 377)		36.50 (10.37)
Racial / ethnic group (*N* = 279)		
African American	224 (59.4)	
Other	105 (37.6)	
White, Caucasian	129 (34.2)	
Biracial/Multiracial	9 (2.4)	
American Indian	4 (1.1)	
Non-black Latino: Puerto Rican	5 (1.3)	
Black Latino: Other	1 (0.3)	
Non-black Latino: Other	1 (0.3)	
Black: Caribbean/West Indian	1 (0.3)	
Other	2 (0.5)	
Educational attainment (*N* = 376)		
Elementary, Junior High	154 (41.0)	
High school and beyond	222 (59.0)	
GED/H.S.	167 (44.4)	
Vocational/Associate/Bachelor	55 (14.6)	
Employment type (*N* = 360)		
Welfare/Gov. Assistance	261 (72.5)	

Other	99 (27.5)	
On Jobs	37 (10.3)	
Other	62 (17.2)	
Treatment type (N = 377)		
In outpatient treatment	258 (68.4)	
In residential treatment	119 (31.6)	
Trauma Symptom Checklist score (N = 375)		44.70 (21.40)
Dual diagnosis (N = 376)*	105 (76.6)	
Generalized anxiety disorder	28 (20.4)	
PTSD	55 (40.1)	
Major depressive episode	81 (59.1)	
Dysthymic disorder	4 (2.9)	
Manic episode	48 (35.0)	
Hypomanic episode	19 (13.9)	
Substances of dependence (N = 372)*		
Cocaine	213 (57.3)	
Alcohol	175 (47.0)	
Marijuana	86 (23.1)	
Opiates	86 (23.1)	
Sedatives	19 (5.1)	
Phencyclidine	12 (3.2)	
Hallucinogens	9 (2.4)	
Amphetamine	4 (1.1)	
Inhalants	1 (0.3)	
Other	4 (1.1)	
Number of substances dependent (N = 372)		1.81 (0.86)
Sobriety over 12 months (N = 304)	178 (47.2%)	

* Percentages for dual diagnosis and substances of dependence do not add up to 100% due to some women being assigned to multiple categories.

Research Question 1a: Latent Profile Analysis

Model selection. I compared models with 1, 2, 3, 4, and 5 classes of social recovery capital. Model fit results are presented in Table 5. Based on model fit, models with 1, 2, and 5 classes were rejected, and models with 3 and 4 classes were compared. While the entropy value for the 3-class model (0.826) was within acceptable limits, it was considerably lower than the values for the 4-class model (0.926). The entropy values provide a summary of the posterior probabilities for the model, and can be affected by a number of things. Because of the large difference between the entropy values between the

3- and 4-class models, I examined the average posterior probabilities (AvePP) for each model. For the 3-class solution, the AvePP s were 0.959 for Class 1, 0.934 for Class 2, and 0.892 for Class 3. Average posterior probabilities for the 4-class solution ranged from 0.924 to 0.991. Per Nagin (Warner, 2013), the AvePP should at least .70 for all groups. Based on the similarity between the ranges of APPs for the 3- and 4-class models, and AvePP values well above the .70 cutoff, I disregarded the entropy values, and considered the two models comparable based on the AvePPs. While the 4-class model performed slightly better than the 3-class model on most model fit statistics, it had one class that represented a low percentage of the overall sample (10%). Models with < 10% of the sample in one class may not be practically useful unless they are represent a clinically important group (Collins & Lanza, 2010). Upon examination of the 4-class model, the class with 10% of the sample did not appear to represent a clinically important group meaningfully distinct from the other classes.

An examination of univariate entropy, or the individual contributions of the social network variables to the total entropy of the latent variable model, showed that density (E=0.446), alters used with (E=0.400), and alter sobriety (E=0.344) contributed the most to distinguishing the classes within the model, while treatment alters (E=0.167), sobriety support (E=0.153), and isolates (E=0.147) contributed less.

Table 5.

Latent profile analysis model fit test results for 2-, 3-, 4-, and 5-class models

Number of classes	LL Value	LMR	*P*	BLRT	*p*	# of classes compared	AIC	BIC	aBIC	Entropy
2	-5492.09	301.18	<0.001	308.436	<0.0001	1 to 2	11022.18	11096.89	11036.61	0.946
3	-5381.57	215.84	<0.001	221.033	<0.001	2 to 3	10815.14	10917.38	10834.89	0.826
4	-5298.80	161.65	0.015	165.539	<0.0001	3 to 4	10663.60	10793.37	10688.67	0.926
5	-5236.15	122.36	0.086	125.311	<0.001*	4 to 5	10552.29	10709.58	10582.67	0.909

Latent typologies identified at study entry. I identified three typologies of social recovery capital identified using LPA and named them as follows. Women in Typology 1 (*n*=54, 14.32%) had higher levels of sober alters and sobriety support, and had few isolates or treatment-related alters. As noted in Chapter 2, having higher numbers of sober and sobriety-supporting alters potentially indicates higher levels of recovery capital (Granfield & Cloud, 2001). The high levels of density in the women's networks in this type as compared to the other types also indicate tightly-knitted, immersive networks that reinforce recovery-oriented norms (Rice & Yoshioka-Maxwell, 2015). While I considered names such as "Highly Connected," the relatively high density and few ties from treatment seen in these women's networks suggested that the women in this group entered treatment surrounded by a close-knit, supportive network that potentially was insulative against recovery threats, leading me to select the name "Insulated Sobriety Support." Women in Typology 2 (*n*=186, 49.34%) also had higher levels of sober alters and sobriety support, but had higher numbers of isolates and treatment alters. This could potentially indicate that these women have access to valuable, novel recovery resources that promote higher levels of social recovery capital (Rivaux et al., 2008; Valente et al., 2004), and led me to name this group "Treatment-Related Sobriety Support." Women in Typology 3 (*n*=137, 36.34%) also had networks with higher numbers of isolates, but had less sobriety support, fewer sober or treatment-related alters, and higher numbers of alters with whom they had used. All of the alter characteristics indicate lower levels of social recovery capital (Granfield & Cloud, 2001), and the high number of isolates indicates less potential for reinforcement of sobriety-oriented ideas (Rice & Yoshioka-Maxwell, 2015), which indicated that the women in this group were "At Risk." The variable characteristics of the 3-class model are presented in Table 6. Post hoc tests using the Bonferroni correction revealed significant differences between groups for all social network variables. The At Risk profile had statistically significantly fewer alters who supported sobriety than the Insulated Sobriety Support (p=.028) or Treatment-Related Sobriety Support profiles (p<.001). Similarly, The At Risk profile had statistically significantly fewer sober alters than the Insulated Sobriety Support (p<.001) or Treatment-Related Sobriety Support profiles (p<.001). The Treatment-Related Sobriety Support profile had significantly more treatment-related alters (peers or professionals) than the Insulated Sobriety Support (p<.001) or At Risk profiles (p<.001). The At Risk profile had significantly more people with whom they had used substances than either other profile, with the Treatment-Related Sobriety Support profile having the fewest (all p<.001). There were significant differences between all profiles for density, with the Insulated Sobriety Support profile having significantly higher density than the Treatment-Related Sobriety Support (p<.001) or At-Risk profiles (p<.001), and the At Risk profile having significantly less density than the Treatment-Related Sobriety Support profile (p=.025). The Insulated Sobriety Support profile had significantly fewer isolates than the Treatment-Related Sobriety Support (p<.001) or At Risk profiles (p<.001).

Table 6.

Social network count variable means for the 3-class model

	1. Insulated Sobriety Support (n=54)	2. Treatment-Related Sobriety Support (n=186)	3. At Risk (n=137)		
	M (sd)	*M (sd)*	*M (sd)*	p	Pair-wise differences†
Sobriety support	19.52 (5.83)	21.18 (3.99)	17.55 (5.00)	<.001	1≠3; 2≠3
Alter sobriety	18.20 (4.76)	19.28 (3.37)	12.21 (3.44)	<.001	1≠3; 2≠3
Treatment-related alters*	1.048 (0.57)	1.50 (0.91)	0.81 (0.76)	<.001	1≠2; 2≠3
Alters "used with"	5.46 (4.12)	3.32 (2.64)	10.56 (3.45)	<.001	1≠2; 1≠3; 2≠3
Network density	0.80 (0.17)	0.19 (0.12)	0.15 (0.11)	<.001	1≠2; 1≠3; 2≠3
Isolates*	0.35 (0.24)	1.74 (0.70)	1.89 (0.74)	<.001	1≠2; 1≠3

*Log-transformed; † Bonferroni correction used

A graphical representation of the z-scores for each social network variable is presented in Figure 3, with the average scores for the overall sample on each variable indicated on the vertical zero axis. The means for each variable broken down by latent profile are indicated in the bars. Variable mean bars that extend to the left indicate means that are below the overall sample mean, and bars extending to the right indicate means that are above the overall sample mean, with the standard deviations from the overall sample mean marked on the X-axis.

Figure 3

Graph of z-scores of estimated means by social recovery capital latent profiles, 3-class model

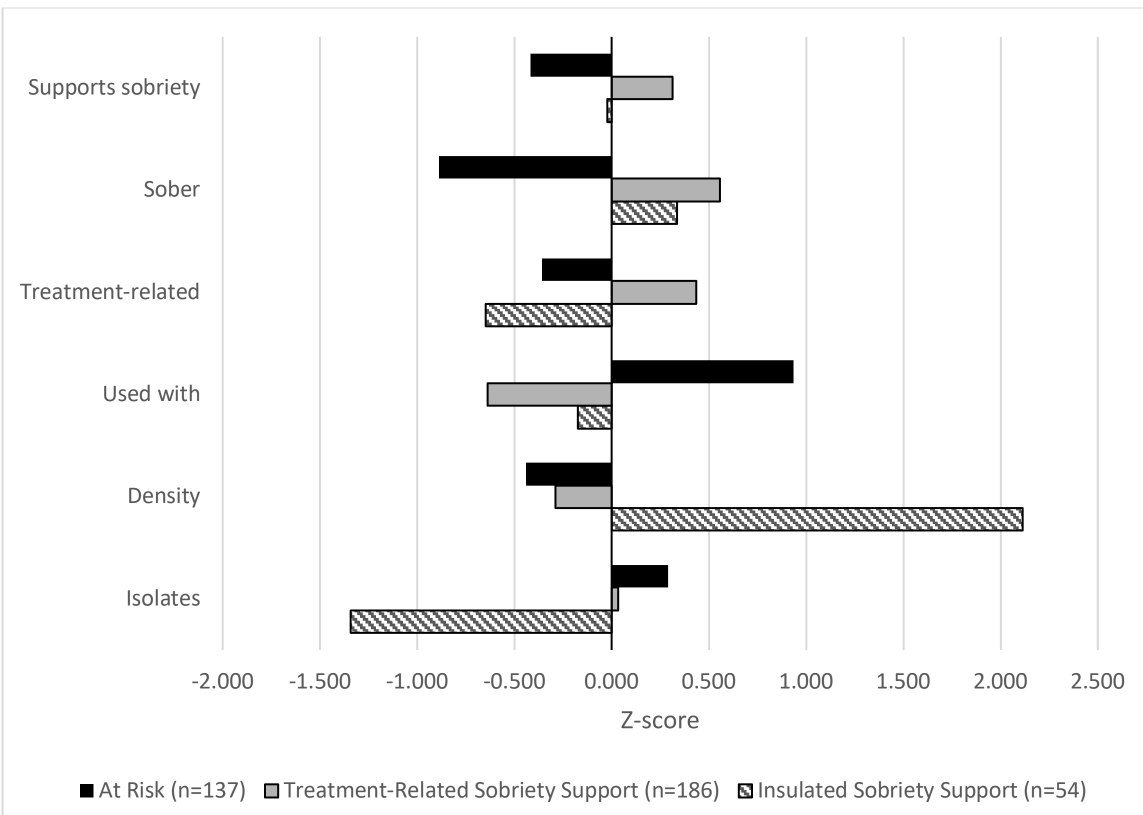


Table 7 shows the average latent class probabilities for most likely latent class membership by latent class, with values on the diagonal indicating of the probability that you have classified an observation into the correct class. A value of 1 represents perfect classification.

Table 7.

Average latent class probabilities for most likely latent class membership (row) by latent class (column)

	Insulated Sobriety Support	Treatment-Related Sobriety Support	At Risk
Insulated Sobriety Support	0.959	0.038	0.003
Treatment-Related Sobriety Support	0.007	0.934	0.058
At Risk	0.002	0.106	0.892

Research Question 1b: Comparison of demographic and clinical variables by latent typology

I separated the sample by latent typology and compared them to determine differences on demographic and clinical variables by latent typology (Table 7). After applying Bonferrroni correction I found statistically significant differences between typologies for age, race, and treatment type. Women in the Treatment-Related Sobriety Support group were significantly older than those in the Insulated Sobriety Support group (t=-2.91, df=238, p=0.004) or the At Risk group (t=3.45, df=321, p=0.001), with an average age of 38.62. There were no statistically significant differences in age between Insulated Sobriety Support and At Risk. While there were no statistically significant differences between Treatment-Related Sobriety Support and At Risk on race, Insulated Sobriety Support had a significantly higher percentage of Black participants than At Risk

(χ^2= 6.99, *df*=1, *p*=0.008). The At Risk group had significantly more participants in residential treatment than Insulated Sobriety Support (χ^2=9.22, *df*=1, *p*=0.002) or Treatment-Related Sobriety Support (χ^2=20.91, *df*=1, *p*<0.001), with no significant differences between Insulated Sobriety Support and Treatment-Related Sobriety Support on treatment type.

Table 8.

Sample characteristics by social recovery capital latent profile

	Profile 1: Insulated recovery support (*n*=54)	Profile 2: Treatment-based recovery support (*n*=186)	Profile 3: At risk (*n*=137)	*p*	Pair-wise difference†
Age, *m* (*sd*)	33.93 (9.59)	38.62 (10.64)	34.64 (9.34)	**<.001**	1≠2; 2≠3
African-American, *n* (%)	40 (74.10)	115 (61.80)	66 (51.8)	**.014**	1≠2; 2≠3
< High school education, *n* (%)	28 (51.90)	66 (35.70)	60 (43.80)	.073	
On public assistance, *n* (%)	43 (81.10)	130 (73.40)	88 (67.70)	.169	
Residential treatment, *m* (*sd*)	12 (22.20)	42 (22.60)	65 (47.40)	**<.001**	1≠3; 2≠3
Dual diagnosis, *n* (%)	32 (60.40)	139 (74.70)	105 (76.60)	.064	

† Bonferroni correction

Research Question 2: Trauma as a covariate

Following the analysis plan described in Chapter 3, I regressed latent profile membership on mean Trauma Symptom Checklist (TSC-40) scores for each identified profile (Table 8). Women in the At Risk typology had statistically significantly higher TSC-40 scores than women in the Insulated Sobriety Support (*B*=0.024, *p* = .007) or

Treatment-Related Sobriety Support (B=0.013, p = .032) typologies. There was no statistically significant difference on TSC-40 scores between the Insulated Sobriety Support and Treatment-Related Sobriety Support typologies.

Table 9.

Trauma as a covariate for social recovery capital latent typologies

	B	SE B	p
Insulated sobriety support	-0.02	0.009	0.007
Treatment-related sobriety support	-0.01	0.006	0.032

Reference group = At risk

Research Question 3: Relation of latent typology membership to sobriety outcomes

I regressed sobriety outcomes on membership in the latent typologies after controlling for significantly-correlated clinical characteristics (treatment modality, dual diagnosis), shown in Table 10. An examination of the clinical variables entered into the regression showed that only dual diagnosis significantly predicted the abstinence outcome (B=-0.99, Wald χ^2=11.97, p = .001; OR=0.37, 95% CI [0.21, 0.65]). Dual diagnosis remained statistically significant after the entry of the typology variables (B=-1.00, Wald χ^2=11.65, p = .001; OR=0.37, 95% CI [0.21, 0.65]). The classification accuracy rate indicated that the model with only the clinical variables in it accurately predicted maintenance of abstinence for 60.7% of the cases, correctly classifying only 27.0% of those who used substances and 84.7% of those who did not. The classification accuracy improved somewhat for the full model, with the overall adjusted classification accuracy rate for predicting maintenance of abstinence rising to 64.0% of the cases, correct classification of those who used substances to 41.3%, and to 80.2% of those who did not. The improvement between the proportional-by-chance classification accuracy rate of the base model of 58.4% and the final model's overall classification accuracy rate of 64.0% indicates that the final model is useful.

Those in the Treatment-Related Sobriety Support typology had 2.094 times higher odds of successfully maintaining sobriety over the first year after entering treatment compared with those in the At-Risk typology (*B*=-0.74, Wald χ^2 =7.486, *df*=1, *p*=.006; OR=2.09, 95% CI [1.23, 3.56]), after controlling for clinical characteristics. There was no statistically significant difference between the Insulated Sobriety Support and At-Risk typologies. Further comparison between the Insulated Sobriety Support and Treatment-Related Sobriety Support typologies showed that there were no significant differences in sobriety outcomes between these two groups.

Table 10.
Logistic regression of self-reported maintenance of sobriety over the first 12 months following treatment entry on social recovery capital latent profiles (N =303)

	Clinical Characteristics			Full Model		
	B	*SE B*	*OR* [95% CI]	*B*	*SE B*	*OR* [95% CI]
In residential treatment	0.38	0.26	1.45 [0.87-2.45]	0.22	0.28	1.25 [0.73-2.14]
Dually diagnosed	-0.99**	0.29	0.37 [0.21-0.65]	-1.0**	0.29	0.37 [0.21-0.65]
Insulated sobriety support				0.35	0.38	1.41 [0.66-3.01]
Treatment-related sobriety support				0.74**	0.27	2.09 [1.23-3.56]
Constant	0.81*	0.31	2.26	0.51	0.34	1.67
-2 *LL*	396.42			388.77		
Model X^2 (*df*)	15.00 (2)**			22.65 (4)***		
Pseudo R^2	0.06			0.10		

* $p < .05$ ** $p < .01$ *** $p < .001$
Reference group = At risk; CI = confidence interval for odds ratio (OR)

Finally, I compared the relative proportions of the sample who were assigned to each social recovery capital latent profile at one week after treatment entry, when the original latent profiles were created, with the sample proportions for each profile at the distal outcome, 12 months after treatment entry. As can be seen in Table 11, the proportions of the sample assigned to each profile remained quite similar despite losing 73 cases to attrition, indicating that attrition occurred equally across the profiles and that no one profile accounted for more attrition than any other. It should be noted that the sample size for the 12-month sample is *n*=304 rather than *n*=303 due to the exclusion of the covariates (treatment program and dual diagnosis) for this analysis.

Table 11.
Comparison of women's social recovery capital latent profile composition at one week after treatment entry versus 12 months after treatment entry

	1 week (*N*=377)		12 months (*N*=304)	
	N	%	*N*	%
Insulated Sobriety Support	53	14.0	44	14.0
Treatment-Related Sobriety Support	190	51.0	158	52.0
At-Risk	133	35.0	103	34.0

Due to the exclusion of the covariates (treatment program and dual diagnosis) for this analysis, the sample size in the 12 month category is *n*=304 rather than *n*=303.

Support for hypotheses.

I found support for all three of my hypotheses. Research Question 1 asked whether there were latent typologies of social recovery capital within the social networks of women who have recently entered treatment for a substance use disorder, and I hypothesized that there would be distinct typologies based on the social network characteristics, and that network structure would play a significant role in defining the typologies. This study found three distinct typologies of social recovery capital in this population: Insulated Sobriety Support, Treatment-Related Sobriety Support, and At Risk. Network structure indeed played a significant role in distinguishing the typologies, with women in the At Risk group having higher numbers of isolates, and women in the Insulated Sobriety Support group having higher network density.

Research Question 2 asked how traumatic symptomatology affects latent typology membership, and hypothesized that higher levels of traumatic symptomatology will increase the probability of membership in latent classes with lower levels of social recovery capital. The women's level of traumatic symptomatology was associated with typology membership, with those in the At Risk group who appeared to have lower levels of social recovery capital having higher levels of trauma.

Research Question 3 explored how latent typology membership predicted the women's ability to maintain sobriety over the first 12 months after entering treatment, and hypothesized that women in who had higher levels of social recovery capital would be better able to maintain their sobriety that those with less. Women in the Treatment-Related Sobriety Support typology could be theorized as having high levels of recovery capital, and did indeed have higher odds of maintaining their sobriety than those in the At Risk typology. A more detailed exploration of these findings and their implications for social work research and practice can be found in Chapter 5, Discussion and Implications.

Chapter 5: Discussion and implications

This dissertation contributes to our understanding of women's recovery from substance use disorders in two primary ways. First, I present a theoretical conceptualization that expands Kelly and Hoeppner's (2015) original model linking recovery capital and the stress-coping model. This expanded conceptualization elaborates on the specific aspects of recovery capital that can be used to support research and practice with women in early recovery from substance use disorders. In essence, this model presents the various domains of recovery capital and the various recovery threats and enablers as lying on a continuum that theoretically changes over time. In addition, this model offers a way to conceptualize how both social networks and the experience and symptoms of trauma affect the recovery process. This type of model is relevant to women in recovery in several ways. As the literature reviewed in Chapter 2 shows, few theoretical models explicitly incorporate aspects of social networks. While recovery capital does incorporate social support in a way that can be conceptualized as social network characteristics and structure (Cloud & Granfield, 2008), merging it with the Stress-Coping model (Lazarus & Folkman, 1984) allows for more complex modeling of the process of appraising coping resources. This is necessary for women in recovery because they tend to have recovery networks that simultaneously support and hinder recovery (Tracy et al., 2010), and need a theoretical approach that can accommodate a complex, whole-network focus. Finally, trauma is repeatedly identified as an important aspect of recovery in the empirical literature (e.g. Sun, 2007; Min, Tracy & Park, 2014), but its relationship to other factors in recovery is not able to be separately explored in the three previously-proposed theoretical models reviewed in this dissertation. It should be noted that only portions of the expanded model presented in Chapter 2 were examined in this dissertation. The situational appraisal and its relationship with trauma were not examined, and nor were domains of recovery capital other than social recovery capital or the longitudinal nature of the process. Potential future research involving these portions of the model will be discussed later in this section.

Second, this dissertation contributes to the empirical literature on the social networks of women in recovery from substance use disorders. I present results from a preliminary testing of this model using latent profile analysis that identified typologies of recovery networks that may be of use in substance use disorder treatment, and related these typologies to both trauma and sobriety outcomes. In support of Hypotheses 1a and 1b, this study found significant variation in alter characteristics and network structure across three latent typologies of social networks among women who have recently entered treatment for substance use disorders. While I found significant differences between the types for all social network variables, the three typologies (Insulated Sobriety Support, Treatment-Related Sobriety Support, and At Risk) differed primarily in three areas: Sobriety of alters and sobriety support; treatment-relatedness of alters; and network structure. First, women in the Insulated Sobriety Support and Treatment-Related Sobriety Support typologies reported statistically significantly higher numbers of alters who were sober or provided sobriety support than those in the At Risk typology. Second, women in the Treatment-Related Sobriety Support typology had statistically significantly higher numbers of alters connected to treatment as either peers in treatment, self-help groups, or professionals providing treatment than women in the other two groups. Finally, women in the Treatment-Related Sobriety Support and At Risk typologies had statistically significantly less-dense networks with higher numbers of isolates than those in the Insulated Sobriety Support group. Taken together, the typologies show three patterns.

Women in the Insulated Sobriety Support typology showed a pattern of a tight-knit network with sober, sobriety-supportive members. Women in this group typically did not report connections to alters from treatment programs or self-help groups, or connections to people with whom they used substances. Women in the Treatment-Related Sobriety Support and At Risk typologies both had more loosely-connected networks with low network density and higher numbers of isolates. The differences between these two groups, however, lie in the number of treatment-related, sober alters, and the number of alters with whom they had used. Women in the Treatment-Related Sobriety Support typology had higher numbers of treatment-related and sober alters, and fewer alters with whom they had used, indicating that the isolates in their networks may represent new connections with treatment-related peers or providers who can provide them with sobriety support. Women in the At Risk typology had few sober or treatment-related alters, and more alters with whom they had used. This suggests that these isolates may either represent the remnants of the women's using networks, or new users with whom the woman has connected through support groups or treatment.

In support of Hypothesis 2, higher mean Trauma Symptom Checklist scores were related to increased likelihood of membership in the At Risk profile for women in this study. This indicates that trauma is an important factor in women's recovery networks, and both theory and prior empirical work suggest that the experience of trauma leads to more recovery-endangering networks (e.g., Cloud & Granfield, 2008; Smith, Davis, &

Fricker-Elhai, 2004; Sun, 2007). This relationship between trauma and women's recovery networks could play out in different ways, though. For example, one woman's prior experience of trauma may make it more difficult for her to form recovery-supportive relationships, as seen in Min, Tracy and Park (2014). Another woman's recovery-unsupportive network may have increased her exposure to trauma, resulting in a cycle of network destabilization, trauma, and substance use, as Gutierres and Van Puymbroek (2006) describe. However, the cross-sectional nature of this analysis makes it impossible to determine the causal ordering of this relationship.

In support of Hypothesis 3, these typologies predicted abstinence outcomes in this examination at 12 months after treatment entry. While there was no statistically significant difference between either sobriety outcome for the Insulated Sobriety Support and Treatment-Related Sobriety Support, women in the At Risk group were significantly less likely to maintain sobriety over the 12 months following treatment entry than those in the Treatment-Related Sobriety Support group, indicating that having treatment-related alters in their networks may be important for women in recovery, particularly if they do not enter treatment with a tightly-knit support network.

While this was not the specific focus of this study, having a co-occurring mental health diagnosis was a significant predictor of inability to maintain sobriety throughout the analyses. These findings were consistent with other research showing the impact of dual diagnosis on sobriety outcomes (e.g. Greenfield, Venner, Kelly, Slaymaker, & Bryan, 2012), and suggest that the presence of co-occurring mental health disorders should be included in analyses of this type.

Implications for social work research.

Both the theoretical conceptualization and the empirical application presented in this dissertation are useful for research and practice with women in the following ways.

Need for theoretical frameworks. Recovery capital is considered to be an emerging perspective in addictions practice that focuses on improving the chances of recovery for the individual by changing the recovery support within their social network as well as the wider community (Mistral, 2013; White, 2009), and yet its framework has not been thoroughly empirically tested. This lack of empirical testing extends to Kelly and Hoeppner's (2015) combined model and the social network-specific model described in this paper. The model presented in this study is intended in part to provide a more comprehensive, testable model of recovery capital. However, like Kelly and Hoeppner's model, the model presented here will need additional empirical testing to determine the exact nature of all of the relationships.

Social networks. While many research studies examine social networks in the context of recovery, few use theoretical models that clearly incorporate the structural aspects of social networks. This is problematic because, as this present analysis demonstrates, network density was shown to be an important predictor for the formation of the latent typologies and ultimately for the sobriety outcome. Examination of the individual contributions of the social network indicators shows that both network compositional and structural variables were integral in the formation of the latent profiles, indicating that both should be considered when using social networks in research.

Trauma. Trauma is also often excluded or incorporated only as a tangential component of models of recovery. In the model presented here, trauma is incorporated as part of the process and shown as affecting multiple aspects of the stress-coping and recovery capital appraisal process. This is in line with current trends in creating trauma-informed systems of care (Substance Abuse and Mental Health Services Administration, 2014a), and with the guidelines proposed for trauma-informed research (Substance Abuse and Mental Health Services Administration, 2014b). The empirical results from research question two demonstrate this relationship, showing that having symptoms of trauma significantly predicts membership in the At Risk typology at treatment entry as compared to the other two typologies.

While this is consistent with previous theory and research regarding the role of trauma in the appraisal process of the Stress-Coping Model (Herman, 1992; Lazarus & Folkman, 1984), it is important to recognize that the findings in this study are very sample-specific, and further testing of the possible mechanism that relates trauma symptoms to the appraisal of social recovery capital for coping needs additional testing in other populations. It may be that this relationship is actually an indirect effect with trauma affecting risk appraisal (Lazarus, 1991) which in turn affects the coping appraisal process, or a multi-dimensional effect, with trauma affecting multiple aspects of the full appraisal process as modeled. Testing of the effects of trauma on the full model with structural equation modeling or a similar analysis is suggested.

Holistic focus. Mirroring the shift in addictions treatment from acute stabilization to one of sustained recovery (White, 2009), there is value in shifting the discussion about recovery from a focus on specific deficits and resources held by a person in recovery to a more holistic focus on how the sum total of the person's individual traits, social network, and other sources of capital work together to promote and sustain recovery. As White

(2009) notes, it is the *ratio* of factors that promote recovery to those that hinder recovery within the person's social world and larger community that is important. Latent profile analyses such as the one presented in this dissertation allow for this holistic focus, and demonstrate the power of such an approach.

The trauma-inclusive social network focus is particularly important for women in recovery, who have been shown to be a special population with specific needs, including the need to examine their social networks holistically. The model and analyses presented here offer a way to examine recovery capital, including social recovery capital, social networks, and trauma, to identify and describe typologies of social networks that support or hinder women's recovery. The model and analyses presented in this dissertation also have implications for practice in the addictions.

Implications for social work practice.

Holistic focus. The social work profession is centered on the holistic view of the person in their environment, and focuses on multiple levels of the person's environment along with their interactions with the environment. The theoretical model presented here honors that central view of social work, and allows the practitioner to examine the interactions between the individual (woman) and the social landscape in which she is embedded. In addition, the use of a continuum to examine positive and negative recovery capital within woman's social network is an essential part of assessing her ability to cope with stressors during recovery. In addition, the use of LPA to determine specific typologies of recovery networks for women mirrors the person-in-environment perspective and presents a practical way to assess the complex dynamics of the social network and tailor treatment according to which recovery network typology matches their situation.

Tailoring treatment. Treatment providers can capitalize on existing supports when creating recovery plans with women. Identifying a client's recovery network typology allows clinicians to precisely target their interventions for women (Lanza & Rhoades, 2013). For example, for women who have sobriety support at treatment entry, clinicians can help them identify their multiple sources of sobriety support, help the woman maintain and strengthen their existing supports, and strategize about the best way to maximize their use of their resources. Women in the At Risk typology have comparatively little network support for recovery, so the primary clinical targets for them suggested by the findings of this study might be to assess what their support needs are overall, identify potential sources of support, provide linkage as needed, and assist them in learning and rehearsing relationship-building skills. An example of an existing therapeutic approach that uses this type of tailored approach is Social Behaviour and Network Therapy, which teaches core skills to strengthen the recovery network such as enhancing social support for recovery (Copello, 2009). Such a strengths-based tailoring of treatment interventions can significantly improve treatment outcomes (Center for Substance Abuse Treatment, 2004), and would need to be tested with this population.

Trauma. Social work practice is increasingly adopting a trauma-informed and trauma-responsive practice model, and having theoretical models that fully incorporate trauma is essential to moving forward into this new practice space. The model presented here shows that it is necessary to assess for trauma and understand the impact that trauma has on various aspects of the client's recovery. In particular, understanding that trauma can change both how a person sees risks and their social recovery capital is important for practitioners in order to provide services tailored to the individual. Trauma is demonstrated empirically in this dissertation to be an important factor in the type of recovery network a woman has. Having more symptoms of trauma predicted membership in the At Risk recovery network typology, and also predicted lower likelihood of maintaining sobriety over the course of the first year after entering treatment.

Clinicians working with women with trauma and substance use disorder issues need to address both in order for treatment to be effective (Najavits, Weiss, & Shaw, 1997). As noted previously, this finding potentially supports a mechanism for how trauma affects a woman's ability to successfully appraise her social network for coping resources. Such a mechanism could be used in practice to educate women on how their traumatic reactions affect their thinking about their recovery network resources and use various therapeutic techniques to change this relationship. There are a number of effective treatment programs that address both aspects of recovery, for example: Seeking Safety, which incorporates modules on successfully using your social network for support (Najavits, 2002), and other combinations of psychosocial, behavioral, and pharmacological treatments (Berenz & Coffey, 2012).

Network structure. Unlike a woman's recovery network composition, network structure is less commonly examined in clinical practice. While a full examination of network structure is beyond the scope of most clinicians, a simple exploration of how tightly-knit a woman's network is (i.e. network density) and whether there are any people that the woman knows that the alters in her network don't know directly (i.e. network isolates) could be helpful. As noted previously, these isolates may either represent bridging ties to recovery resources or to recovery-endangering groups (Granovetter, 1973; Valente et al., 2004), and identifying these potential resources or pitfalls is clinically useful. Using this information, clinicians may either teach clients how to enforce boundaries with recovery-endangering ties, or how to leverage recovery-supportive bridging ties to support their sobriety. Examples of therapeutic approaches that utilize this method are Twelve-Step Facilitation or Network Support Therapy (Litt, Kadden, & Tennen, 2015). For clients with relatively dense, recovery-supportive networks, using therapeutic approaches that engage the client's family or support-network may be beneficial, as such dense networks can provide a reinforcement of recovery-supportive ideas for the client. However, very dense networks can resist innovation (Valente, 2010), so clients with dense networks could benefit from linkage to novel sources of recovery support in order to further strengthen the recovery-supportiveness of their networks.

Multiple paths to recovery. There are multiple paths to recovery (White & Cloud, 2008), and it stands to reason that varying combinations of network characteristics may all lead to successful recovery for women. Treatment providers cannot assume that just because someone has a substance use disorder, they don't have sobriety support. As can be seen in both the Insulated Sobriety Support and Treatment-Related Sobriety Support typologies, women can have robust support systems very early in treatment that are linked to positive sobriety outcomes in the long term.

This individualized approach is important because each woman's experience of recovery is unique and there is a need to assess longitudinally and holistically for individual aspects of the person's social network at the start of recovery and at various points over their early recovery. There is support for this type of approach in the Recovery Support Strategic Initiative established by the Substance Abuse and Mental Health Services Administration that has also emphasized the need for treatments for substance use disorders that mobilize and strengthen the social resources available in the social networks of people in recovery, particularly in ways that are individualized (SAMHSA, 2015). Correspondingly, there is a strong need for theoretical models that use a longitudinal and holistic approach to support research and practice for women with substance use disorders.

Strengths and limitations.

This dissertation has many strengths. First, the expansion of the theoretical model contributes to theory development by elucidating three areas that have not been clearly theoretically defined for women in recovery from substance use disorders: the contribution of trauma, how social network analysis can be integrated into a theoretical framework, and the longitudinal modeling of recovery. While this dissertation only tests certain relationships posited in the expanded model (see shaded areas of the model in Figure 1), it lays the groundwork for further research focused in the area of women's recovery from substance use disorders.

My empirical results demonstrate that the relationships posited by Kelly & Hoeppner (2015) and expanded on in this dissertation are testable and do successfully model aspects of women's recovery. In particular, modeling the evaluation of coping resources as an evaluation of the woman's recovery network characteristics as a whole was supported by the successful identification of latent typologies in relation to abstinence outcomes. Likewise, including trauma as a covariate to the formation of these typologies showed how inter-related trauma is to the process of evaluating social recovery capital as a coping resource.

The findings in this dissertation were also consistent with Granovetter's theoretical work regarding the strength of weak ties (1973). Women in the At Risk group had comparatively more isolates than women in the other two groups, and they were less able to maintain their sobriety over the course of the year following treatment entry. Within the recovery capital framework, bridging ties do not necessarily need to be recovery-supportive, but merely need to be connections to resources. Thus, these network isolates, or "weak ties," seen in the At Risk type could be bridges to recovery-supportive or recovery-endangering resources. For example, the isolates in the networks could easily be people who are recovery endangerers such as people with whom the woman uses, but could also be the seeds of a new, more recovery-supportive network such as a sponsor or therapist. This finding regarding isolates leads to questions about the exact recovery-supportive or recovery-endangering characteristics of these potential bridges which cannot be determined using latent profile analysis. In addition, bridging ties are typically discussed in terms of linking a person to positive supports, and this finding indicates that the isolates in the At Risk group may be links to resources that reduce recovery capital. If this is so, further research is needed on how we can leverage bridging ties to increase recovery capital, including specific ways to form bridging ties that are supportive of recovery.

Second, LPA methodology with count variables of social network characteristics has not been fully explored in previous studies. As noted in Chapter 2, categorization of count variables collapses the rich detail that is the advantage of using social network data in analyses. This dissertation provides a model for future research using this method. Likewise, the inclusion of structural variables is under-explored in analyses using social network data, and particularly in latent variable analyses. Because the analyses and theoretical conceptualizations presented here indicate that structural variables may play an important role in recovery networks, this is an important addition to the literature.

This dissertation also demonstrates that trauma is an important covariate to include in latent variable analyses with this population. Additionally, the role of trauma in predicting membership in the recovery typologies identified has practical implications for clinical work, as described above. Finally, this dissertation focuses on an under-studied population: low-income, racially-diverse women in recovery with trauma exposure and dual disorders.

However, this study had several limitations. First, the sample size for this study ($N = 377$) is somewhat low. However, the entropy and the average posterior probabilities indicate that this LPA model has sufficient power to clearly distinguish the classes (Warner, 2013). Similarly, while this study did relate typologies to long-term (12 month) outcomes, it was primarily cross-sectional in nature. It is possible that membership in these latent recovery typologies changes over time, and that is an area for future research using latent transition analysis (Collins & Lanza, 2010). In addition, as was identified in the literature review, network size has been previously linked to sobriety outcomes. This study limited participants to providing exactly 25 names, so there was no way to examine variations in network size. This limitation is also a strength, though, as 25 alters has been determined as the minimum network size to obtain a valid density score (McCarty, Bernard, Killworth, Shelley, & Johnsen, 1997), an important variable in this analysis.

Another limitation is that there is no way to identify the combinations of individual alter characteristics with this type of analysis. So, for example, there is no way using latent profile analysis to determine whether the network isolates are actually treatment-related individuals or substance users, and thus we cannot test this aspect of the theory using this methodology. Other potential ways to measure this are explored in the next section (Future Research).

Likewise, due to low numbers in the variables for treatment-related peers and treatment-related professionals, these variables were combined into one variable, treatment-related alters. From theoretical and empirical literature, we would expect that these two groups would provide qualitatively different support for recovery. In addition, the question about treatment-related peers did not distinguish between peers from self-help programs (e.g. AA/NA) or treatment programs. Both of these may be meaningful distinctions worthy of exploration.

Finally, there is a general limitation of inconsistent social network measures across the literature on recovery from substance use disorders. Often, studies use less numerically-driven measures of social networks that don't allow for the examination of network structure (Tracy & Whittaker, 2015). Studies in this area also use a variety of measures of social support and the level substance use of the network alters. This makes comparison across samples quite difficult. Latent profile analysis is a highly sample-specific methodology, a limitation in its own right, and being able to compare the values of the social network variables observed in this sample with those observed in other samples would have increased the generalizability of this study.

Future research.

This dissertation identified and related typologies of social recovery capital to both trauma and abstinence outcomes among a population of low-income, racially-diverse women in early recovery from substance use disorders. There are potential several areas for future research suggested by the findings, strengths, and limitations.

First, while this dissertation examined membership in three social recovery typologies at the women's entry into treatment and related this to a sobriety outcome 12 months later, this study was not a truly longitudinal design. Future research should examine how women transition between the social recovery network typologies over the course of their recovery, and whether this is related to sobriety outcomes at various time points over the 12-month time period explored here, or over a longer time frame. Laudet and White (2010, 2008) present a set of stages for the first three years of recovery which could be modeled and tested empirically using latent transition analysis. In general, extending the study of recovery longitudinally to at least 3-5 years is recommended (Dennis, Scott, Funk, & Foss, 2005), and could provide more information about successful strategies for long-term recovery.

Similarly, a finer-grained, longitudinal examination of the exact characteristics of the network members and how and when they enter and leave the network using dynamic social network analysis or a similar analysis type could provide more information about who the network isolates are. Similarly, logistic multilevel analysis has been used to measure the strength and persistence of ties over time (Lubbers et al., 2010), and could be used to determine how relationships with various network members evolve over the course of recovery, and how that affects long-term sobriety. The Convoy Model of Social Relations (Antonucci, 2001), which theorizes that close network ties form a convoy of support for a person going through a life change such as retirement, or, in the case of this dissertation, transitioning into recovery after substance use. This theory has been tested using latent class analysis (Kim, Park, & Antonucci, 2016), and may be an important addition that can explain both the longitudinal process of transitioning between the identified recovery network profiles and how network member movement into and out of the network affects the recovery process.

Research question 2 of this dissertation explored the relationship of trauma to membership in the social recovery capital typologies, measured at the initial time point. It is probable that women in the study experienced further traumatic events during the course of the 12-month time period, particularly among those who have previous high levels of trauma, or who have relapsed (Harris, Fallot, & Berley, 2005). Future research that examines this complex relationship is suggested.

The inability to compare this sample with other samples on the social network measures was noted previously as a limitation, but it provides an opportunity for future research as well. Testing whether the same typologies are identified for other samples of women or other demographic groups would increase the generalizability of this study, making it possible to formulate effective treatment interventions based on social recovery capital typologies.

In addition, this study identified that age, race, treatment type (residential versus outpatient), and level of traumatic symptomatology differed between the three typologies. It is probable that treatment type is a proxy for addiction severity (Dodge & Potocky, 2000), and that age may be related to the number of episodes of previous treatment (Dennis, Scott, Funk, & Foss, 2005), and trauma is a known complicating factor for addiction recovery. Likewise, dual diagnosis significantly predicted abstinence outcomes in the regression, consistent with prior research (e.g. Greenfield, Venner, Kelly, Slaymaker, & Bryan, 2012). All of these covariates warrant further investigation into how they affect both initial membership in a recovery typology, and transitions between typologies over time.

The significance of these specific covariates also point to the need to empirically test other domains of recovery capital within the model. For example, under Cloud and Granfield's (2008) model, variables like race, income source, and treatment type can be conceptualized as either cultural or environmental (physical) capital. While the distinction between the classification of these variables may not affect sobriety outcomes—they all represent parts of recovery capital—it may be important to clearly identify the distinctions in order to understand how best to support an individual in recovery. For example, if income source plays a significant role in recovery capital for this population, assisting people in finding more stable income could become an intervention target. In addition, various biological factors may be important to consider. Medication-assisted treatment of substance use disorders has been linked to increased recovery capital and improved ability to maintain sobriety (Nutt, 2015). Psychiatric medications such as antidepressants may affect the appraisal process by improving the self-appraisal of coping ability and self-efficacy (McCusker et al., 2016), potentially altering the impact of trauma and dual diagnoses on the appraisal processes, or affecting the ability to maintain sobriety. Such biological factors may play a role in defining recovery network profiles, and these relationships should be explored.

Finally, given that recovery capital is a theory under development (Cloud & Granfield, 2008), qualitative or mixed-methods research that explores how women view both the recovery-supportiveness of their network characteristics and their own process of considering their social network when appraising their ability to cope is indicated. This type of analysis has the potential to provide a richness of experience and to help uncover the mechanisms for social network change (Tracy & Whittaker, 2015). Most importantly, it allows researchers to center the women's experiences within our work.

Conclusions.

This dissertation provides a needed expansion of theoretical models that better explain how social networks and trauma function within women's recovery from substance use disorders, and addresses the identified need for theoretical models that use a longitudinal and holistic approach. The model presented here illuminates key factors in women's recovery process that have the potential to support trauma- and social-network-informed interventions.

Additionally, the empirical analyses presented in this dissertation provide a significant contribution to the literature in three ways. First, this study expands our knowledge of the role that network structure plays in recovery among women, indicating that network isolates may represent key structural elements that can be leveraged to support recovery. This study also provides a more holistic view of women's recovery networks, allowing us to examine the patterns in recovery networks that support or hinder women's recovery from substance use disorders. Finally, the identified typologies can provide a clinically-useful starting point for research on individualized, targeted, and trauma-responsive interventions for women in recovery. Such a clinical intervention or module could incorporate simple social network analysis, education on multiple paths to successful recovery, and strategies for increasing the recovery-supportiveness of women’s networks, and could be used to complement traditional interventions in substance use recovery.

Appendix A: Additional information about Latent Profile Analysis

LPA has two main assumptions: 1) the assumption of multivariate normality for the indicators within each typology, and 2) the assumption of local or conditional independence (Tein, Coxe, & Cham, 2013). The assumption of multivariate normality will be tested by examining the multivariate distributional characteristics within each identified class via the critical ratio of the multivariate kurtosis index with problematic non-normality indicated at >10.0, and serious non-normality indicated at >20.0 (Kline, 2016, pp. 76-77). The assumption of local independence states that, "…conditional on the latent variable, the observed variables are independent," and that this independence "…is assumed to hold only within each latent class" (Collins & Lanza, 2010, p. 45, 46). For practical purposes, the assumption of local independence means that the errors of the indicators of the latent variable cannot be correlated.

Notation of parameters

Parameters for LPA (Lubke & Neale, 2006; Peugh & Fan, 2013) include:

- Latent variable: *L*, the underlying construct driving membership in classes.
- Observed indicators: *y*, the observed social network variables.
- Observed individual responses: *i*
- Latent profiles: *K*, the various typologies of the underlying construct represented within the sample. In theory, all possible latent profiles will be represented at the population level; however, some profiles of the latent variable may not be represented at the sample level due to individual variations.
- Profile density: π_k (*pi*), the proportion of the total *N* respondents that are members of a specific profile. Can be also described as the prior probability of belonging to

latent profile *k*, and the values for π_k sum to 1 across the various classes (Pastor, Barron, Miller, & Davis, 2007).

- Item response means and variances: μ_{ik} (*mu*), σ^2_{ik} (*sigma*) the profile-specific means and variances for the observed indicators (y).
- Latent profile covariance matrices: Σ_k , the profile-specific covariance matrix for the observed indicators (*i*).

The model for latent profile analysis can be found in Figure 2. The equation for the LPA model, as described in Peugh and Fan (2013), is as follows:

$$\sigma_i^2 = \sum_{k=1}^{K} \pi_k \, (\mu_{ik} - \mu_i)^2 + \sum_{k=1}^{K} \pi_k \, \sigma_{ik}^2$$

This model assumes that the population from which the sample is drawn is heterogeneous and contains latent profiles, and that the distributions of the indicators are normally distributed within each profile (Peugh & Fan, 2013). Additional assumptions for the LPA model commonly operationalized with model constraints include the assumption of local independence and the assumption of homogeneity across latent profiles (Lubke & Neale, 2006; Peugh & Fan, 2013). These constraints result in modifications to the model equation as shown below.

Model constraints

Latent profile models are minimally identified with *df* ≥ 1. Model constraints are imposed in LPA to reduce the number of estimated parameters in order to aid in model identification. Using the framework provided by Peugh and Fan (2013) and Lubke and

Neale (2006), constraint of the LPA model for the assumption of local independence is typically accomplished by constraining all elements of the covariance matrix off of the diagonal to be zero. While assuming homogeneity across latent profiles is not an actual assumption necessary within LPA, it is a typically-imposed model constraint that involves setting all profile-specific elements on the diagonal of the covariance matrix to be equal among all latent profiles. In essence, these two constraints force the model to focus on the respective locations of the indicators within the latent profiles, allowing for classification. This simplifies the model equation, essentially reducing it to a posterior probability function:

$$f(y) = \sum_{k=1}^{K} \pi_k f(y_k)$$

Parameter estimation

Two parameters are of particular interest in LPA: the profile-specific item-response means and variances, and the posterior probabilities of membership in a latent profile.

The patterns of the profile-specific item-response means and variances are used to determine the number and composition of the latent profiles identified during LPA (Lubke & Neale, 2006). These patterns are interpreted and used in naming the typologies, with high response probabilities on one item indicating that this item is characteristic of the profile (e.g. if a profile shows a high mean score on Indicator 1 and a low mean score on Indicator 2, a profile name might be, “High Indicator 1”). Determinations of “high” and “low” are completed using a comparison of the patterns across latent profiles (Collins & Lanza, 2010).

The posterior probability of membership in a latent profile is the probability that an individual case will be a member of a specific latent profile using Bayesian prediction, and ranges from 0.00 to 1.00 (Collins & Lanza, 2010). Posterior probabilities are calculated using the observed means and variances, and, at the individual level, the probabilities for a single individual across all typologies should sum to 1. Classification certainty is the likelihood that you will be able to predict an individual's latent class membership from their observed response pattern. There is always some level of classification uncertainty because of measurement error, but ideally it should be closer to 1.

From the posterior probabilities, several additional pieces of information can be derived. First, the mean posterior probability and its standard deviation provides a profile-specific measure of how well the observed indicators predict latent profile membership (Collins & Lanza, 2010). Likewise, the odds of correct classification (OCC) provides an odds ratio of the model's accuracy in predicting profile membership, with an OCC = 1.00 indicating even odds, and an OCC of ≥ 5 indicating good separation of profiles (Collins & Lanza, 2010). It should be noted that MPlus currently does not calculate the OCC as part of the 3-step LPA program. For this reason, the average latent class probabilities for most likely latent class membership by latent class is provided instead, with higher values on the diagonal indicating better classification of cases. Lastly, entropy is the weighted average of the individual posterior probabilities (range: 0 to 1), with higher values indicating less entropy, and consequently better prediction of class membership (Collins & Lanza, 2010).

Parameters in LPA are typically estimated using maximum likelihood (ML) estimation, which iteratively estimates parameter values for which the data has the greatest likelihood of being observed (Collins & Lanza, 2010). The log likelihood value derived from this indicates model convergence, and the model is deemed to have reached convergence when the maximum absolute deviation (MAD) value ≤ .000001 (Collins & Lanza, 2010, pp. 78-79).

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