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Types Of Types: Social Network Typologies and Meaning of Clients With Serious Mental Illness

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TYPES OF TYPES: SOCIAL NETWORK TYPOLOGIES AND MEANING OF CLIENTS WITH SERIOUS MENTAL ILLNESS

by

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Under the Direction of Eric R. Wright, PhD

ABSTRACT

The relationship between clients with serious mental illness (SMI) and their staff members is multifaceted and complex. Using data from the Indiana Mental Health Services and HIV Risk Study, I investigate the personal networks of clients in community mental health centers (CMHC) and state psychiatric hospitals (SPH). Clustering analysis reveals five distinct network types derived from structural and functional measures of client's ties; supportive context, diverse context, sparse context, clinical context, and treatment-focused context. In addition, weighted least squares regressions show the association of client's network types onto their working alliance with staff members. Indicating, clients with treatment-focused networks predict the weakest working alliance compared to other network types. This study contributes insights to the emerging relational sociology approach by exploring the meaning of social ties in personal networks using quantitative analysis.

INDEX WORDS: Serious mental illness, Social networks, Treatment, Relational sociology

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1 INTRODUCTION

"To speak of social life is to speak of the association between people- their associating in work and in play, in love and in war, to trade or to worship, to help or to hinder. It is in the social relations men established that their interests find expression and their desires become realized."

Peter M. Blau

Exchange and Power in Social Life, 1964.

The structural and functional features of personal networks are powerful indicators of mental health and treatment outcomes (Fiori, Antonucci, Cortina 2006; Lin and Peek 1999; Pescosoldio 1991; Pescosoldio and Boyer 1999; Schafer 2013). The proliferation of network analysis throughout the physical and social sciences along with the rapid development in multivariate analytical techniques has allowed researchers to intensely examine social network structures (Scott 2017; Pescosoldio and Levy 2002). The emphasis of variable centered research in social network analysis and the roles actors play are firmly established to have substantial influence upon the individual (Marsden and Friedkin 1994; Smith and Christakis 2008). The increasing complexity of network analysis comes with greater reliance on theory to parse out how mechanisms within networks operate and their consequences onto the individual. One aspect of networks long overdue for intense examination is culture. A core principle of sociology, although difficult to define in of itself, the role of meaning in personal networks is one of a "culture gap" (Emirbayer and Goodwin 1994) in research (Perry, Pescosoldio, and Borgatti 2018). The meaning *within*, *about*, and *of* networks is largely unknown and continues to be largely avoided by network analysist and cultural experts (DiMaggio 2011). One place culture has significant consequences on individuals is within treatment setting of clients with serious mental illness (SMI). The surrounding clinical culture of treatment influences the attitudes of clients and staff members on sexual expression and HIV/AIDS (Wright 2001). Further, investigating the meaning of social relations between client and staff may provide insights into the culture of care for clients with SMI and inform treatment program development.

In this study, I set out to investigate the egocentric networks—personal networks arranged around a single person (e.g. the ego) from their perspective—of clients with SMI in the treatment system using the Indiana Mental Health Services and HIV Risk Study (Wright 1999). I use the personal networks of clients receiving treatment in community mental health centers (CMHC) and state psychiatric hospitals (SPH) to investigate if distinct and unique network types exist. Next, I test the association between network types and their working alliance—the therapeutic relationship between the client and staff member with the specific goal on improving the client's situation. By using a quantitative methods approach with in-depth survey data, I can examine if network types have implications for client-level outcomes. My analysis is guided by the following questions; are there different network types of clients in the treatment system?; do network types have implications for client-level measures?; what role does meaning have on influencing individuals in a network?; and finally, what can the meaning of ties tell us about clients with SMI in treatment? I address these questions using cross-sectional egocentric network data and two types of quantitative analyses to examine the association of network types to the client-staff relationship.

1.1 Review of Literature

In this section, I first discuss the relevant literature on personal network typologies, the components used to analyze them, and the importance of social networks on client's working alliance with staff members. Next, I highlight the types of contacts clients have in the treatment system, focusing on their internal and external ties. Third, I review the client-staff working alliance and contributing factors. Finally, I describe the relational sociology approach and how it may be useful for examining meaning in personal networks of clients with SMI.

1.1.1 Social Network Typologies

Over the last twenty years, social network analysis and the social sciences have drifted away from typological research in favor of multivariate research designs (Scott 2017; Pescosoldio and Levy 2002). Recently, calls to revisit network typologies and their potential for theoretical development and testing are rising (Crossley et al. 2015; Fiori et al. 2006; Fiori, Antonucci, and Cortina 2007; Perry et al. 2018). Network typologies are classifications of multiple observations, often with multiple variables, into distinct “profiles” (McCarty et al. 2019) or contexts. Beginning with Simmel’s (1955) seminal description of social forms and their consequences onto the individual, network typologies are at the core of how sociologists, make sense of social structures and their functions (Chau, Madej, and Wellman 2011; Litwin 2001; Pescosolido and Rubin 2000; Wegner 1997; Wellman and Potter 1999). Based on structure alone, computer simulations have identified network typologies (e.g., small world and scale-free networks) and tested them using real world data. Researchers have found examples of simulated network structures across domains in biology, server systems, and air travel (Albert and Barabasi 2002; Watts and Strogatz 1998). Additionally, the use of mix of methodologies (e.g., surveys, interviews, text, and ethnographic observation) for personal network data collection has allowed researchers to understand network types beyond structural measures to consider the construction, dynamics, and meaning in networks (Bellotti 2014; Edwards 2010).

Empirically, network typological research focuses on identifying the *types* of personal networks with a series of measures including structure (e.g., size and density), function (e.g., social support or information), and composition (e.g., friend or family networks). Wellman and Potter (1999) determined four key elements in personal network communities of residents in Toronto; immediate kinship/friendship, contact, range (i.e. the size of the network and the degree of heterogeneity), and intimacy that 'build' different network types. Research into the personal networks of older adults consistently finds four network types arranged around the individual; diverse, friend-focused, family-focused, and restrictive (Bosworth and Schaie 1997; Fiori et al. 2007; Litwin 1997, 2000, 2001, 2011b; Wenger 1997). Mostly constructed from structural and compositional measures, these network types are robust patterns of social relations because they appear across nationalities, cultures, and social contexts. While variations do exist across studies, this is often due to the availability of certain variables in the datasets such as older adults' neighborhood and physical distance between ties. The need to include relevant network variables for each population to derive network typologies often makes comparison across studies difficult (Fiori et al. 2007; Litwin 1997, 2000).

In addition to network construction, evidence shows that networks types have implications for individual level outcomes, such as health (Litwin and Shiovitz-Ezra 2011a, 2011b; Li and Zhang 2015; Santini et al. 2015). Fiori et al. (2006) finds that older adults with diverse networks—characteristic of frequent contact with a range of social ties and regular attendance at social events—were associated with less depressive symptomatology when compared to older adults with restrictive networks—small and infrequent contact with social ties and low attendance at social events. This illustrates personal networks as 'pools' of resources having implications for individual level characteristics such as mental health.

Examining network types against non-network measures showcases the multidimensional approach as a means to test the network not just the components that make up networks. While studies continue to confirm and discover new network types in the community, questions remain if network typologies are consistent across all social domains, especially considering the influential role the treatment system has on clients ability to form connections and relationships in and out of treatment (Dobransky 2017). The present study expands previous network typological research to include additional aspects of human relations, such as sexual support and treatment support between clients and staff members (Chronister et al. 2016; Wright et al. 2006).

1.1.2 Social Networks and Clients with Serious Mental Illness

Clients are embedded in networks. Clients with SMI have smaller social networks than persons without SMI (Harris, Brown, and Robinson 1999; Walsh and Connelly 1999). Clients with SMI networks primarily consist of mental health professionals, other clients, and core family members (Angell 2003**;** Borge et al. 1999**;** Dailey et al. 2000**;** Meeks and Murrell 1994) and are less integrated into the community (Davidson et al. 2004). The degree to which clients are integrated in social networks, whole or personal, contribute to the pathways and effectiveness of treatment (Alang and McAlpine 2019; Albert et al. 1998; Pescosolido 1992; Pescosolido, Gardner, and Lubell 1998; Vogel et al. 2007; Wright et al. 2006). Studies examining networks in the treatment system identify two types of client ties: internal and external ties. Internal ties are the connections clients develop with staff members and other clients in the treatment facility. Establishing internal ties leads to better internal integration. Clients embeddedness in the mental health system improves tolerance toward clients and creates a social safety net (Dobransky 2014). In addition, the attitudes and beliefs held by staff members play a large role in defining the climate of care during treatment, having consequential effects on clients. Staff members exert a great deal of influence on clients to change behavior, direct treatment, and build social relations (Wright 2001), raising further questions of how clients perceive the structural arrangements and functions of their internal ties during treatment.

On the other hand, external ties are client's connections to the community such as family, friends, and other professionals outside of the treatment setting. External integration is a key factor in how clients enter the treatment system through supportive or dismissive networks (Pescosolido 1999). Supportive external ties have also been found to increase health care utilization and improve treatment outcomes (Schafer 2013; Perlick et al. 2005; Wenger 1997). For example, Chronister's and colleagues (2016) study of social support clusters among clients with psychiatric disabilities in CMHCs demonstrate the implications of external social support to recovery. Clients embedded in networks with high social-support report greater quality of life, lower rates of loneliness, reduced symptom distress, and improved levels of mental health recovery compared to those embedded in lower social-support networks. Thus, client's ties in the community play a significant role in the processes of recovery, where clients rely on the community for support and wellbeing.

In addition, the deinstitutionalized era and now post-deinstitutionalized era of mental health treatment have brought on a number of challenges. The fragmentation of services (Dobransky 2014) and increasing reliance of external support place greater strain on the community to care for those effected by SMI (Scheid 2004). Perry and Pescosolido (2010, 2015) present evidence that clients may activate specific external ties when confronted with an illness crisis, demonstrating that clients are able to draw on their ties to supply a specific function (McConnell and Perry 2016) for resources (e.g., social support or health support). The mentioned study is part of the broader trend in the mental health and social support literature, where an increased focus on the functions of network ties in conjunction with the structural arrangements of ties broadens the understanding of influence in networks. Many studies draw from Weiss's (1974) functional specificity hypothesis, which contends that persons fulfill an explicit purpose to individuals (Fiori et al. 2006, 2007; Perry and Pescosolido 2010). Research into the dynamics of client's networks in the treatment system have shown that personal networks experience notable change overtime. Where the functionality of external ties is most active during initial stages of the illness career, these are replaced over time by internal ties, as family and friends recede out of the network (Perry and Pescosolido 2010).

1.1.3 The Client and Staff Relationship

In the vast literature on therapeutic alliance and treatment outcomes, two key actors are the focus: the client and the staff member. While the exact definition of a therapeutic alliance varies across the developed measures, they all stem from Bordin's (1979) conception that it is the collaborative relationship between client and staff to improve the situation of the client's suffering. Studies continually demonstrate the links between the therapeutic alliance and therapy outcomes **(**see Ardito and Rabellino 2011; see Elvins and Green 2008; Horvath 2001; see Martin, Garske, and Davis 2000) and ask: what are the characteristics of staff members and clients that affect the therapeutic alliance?; and what are the implications of the working alliance for therapy outcomes? This dyad centered perspective provides insight into the therapy experience from both the client and staff member, to understand the consequences of the therapeutic relationship. Empirically, studies into the therapeutic alliance focus on staff characteristics, such as trustworthiness (Horvath and Greenberg 1989), level of education (Mallinckrodt and Nelson 1991), therapeutic orientation (Black et al. 2005) and point to the development of positive and negative alliances (see Ackerman and Hilsenroth 2001a, 2001b). For example, Dobransky's

(2014) account of treatment in CMHCs finds that staff members with less advanced clinical training tended to relate to clients through personal experiences compared to clinically trained staff members. Staff members with advanced training were more prone to conduct an “abstract analysis of client’s situations” (2014:130). Whereas in negotiations of drug prescription, the client’s belief in the staff member is the basis for the alliance not necessarily the professionals training (Karp 2006). These highlight the fact that client’s perception of staff members to trust, be open, and willingness to collaborate is crucial to developing a positive therapeutic alliance. Additionally, the type of treatment setting can explain differences in roles and approaches staff members take on during treatment (Wright and Gayman 2005; Wright and Martin 2003; Scheid 2004), suggesting that therapeutic alliances may vary across CMHCs and SPHs. Consequently, I test client’s working alliance across treatment facilities for differences.

1.1.4 Meaning and Networks

Affecting the illness experience of clients are the held attitudes, beliefs, and norms of staff members (i.e. client’s therapeutic alliance). In this section, I review the relevant literature on meaning in networks and how meaning may be useful in examining client’s personal networks. Attempts to examine meaning within networks have generally been avoided by traditional network analysis (DiMaggio 2011; Emirbayer 1997; Fuhse and Mützel 2011). Meaning in networks is subjective and requires qualitative methods to tap into “the process of creating, sustaining, and modifying this meaning” through communication and individual’s motivations (Fuhse and Mützel 2011:1078). Whereas the traditional conception of a network is a structure with a number of actors that are adjacent to each other by a series of ties and a finite definition of components (e.g., nodes, edges, dyads, and triads) (Wasserman and Faust 1994).

The tension between conceptions away from a purely structural approach of a ‘connection’ to include meaning has led some to reconceptualize what a network is.

A push by cultural scholars, social network analysts, and others are making progress on investigating the “intersections” between meaning and networks (McLean 2016). One approach with promise is the emerging relational sociology (White 1992, 2008). Resting on the notion that networks are not just structural units (McLean 2016) rather constituting actors as “always in-relation” (Crossley 2015:69) to one another in an ongoing process. In this conception, client’s take on their own meanings and identities through communication and interaction. The relational sociology approach is further differentiated from the structural approach as traditional network analysis examines the composition of beliefs of actors and dubs this the ‘cultural content’ (i.e. social capital) in a network. The relational sociology approach surmounts a simple count or proportion of beliefs and/or attitudes held by actors may be the acquired elements of culture, but rather the process of interaction derives culture itself (Crossley 2015).

The challenge, then, of merging network analysis and the study of meaning is addressed by using mixed method designs. For example, Bellotti’s (2008) empirical analysis of personal friendship networks among single individuals in Italy derives four network types using structural network analysis and in-depth interviews. Asking participants to name their friends without providing a definition of what a friend is, the histories of ties between alters determined that the subjective meaning of friendship varies across the ego’s characteristics. Thus, only conducting a structural network analysis would require a social capital definition of friendship, which was not supported in the qualitative findings (Bellotti 2008). These findings provide insight into the various conceptions of what friendship could be. Earlier research examining the relations of cultural objects have mapped the connections between individuals and/or text through shared affiliations or attributes (Hill and Carley 1999; Krinsky 2010; Mohr 2013). Taking on a different angle, Pescosolido and Wright (2004) examined overlap in client's networks and attributed discrepancies in network reporting as indictors of difference in meaning rather than issues in recall. Their results show the name generators used to collect network data and the meaning individuals attribute to concepts of health support during an illness crisis, plays a crucial role in the construction of networks.

Although, in the present study, I do not use qualitative methods, nor do I have longitudinal data, relational sociology provides a basis to theorize about the meaning of staff members to clients in treatment beyond their role to treat. For example, staff members perceived to supply sexual support, an intimate topic one would expect discussions to occur mostly with core network members, is an indicator the staff member is a close confidant to the client. Where supplying a specific type of emotional support in addition to treatment changes the meaning of a staff member from strictly treatment provider to an emotional supporter who treats. By supplying support to other aspects effected by client's illness, staff members define the culture of care which have consequences onto the client. It must be noted, however, that all the variables in this study are reduced to the client-level and thus a truly relational sociology approach cannot be done, but insights into the meaning of staff members to clients may be gleaned.

2 THEORETICAL FRAMEWORK AND RESEARCH QUESTIONS

2.1 Social Forms

My theoretical starting point is Simmel's social forms (1955). Theorized for premodern, modern, and extended by Pescosolido and Rubin (2000) for the contemporary era, Simmel's (1955) social forms describe the geometry of daily life. Each form represents a distinct type of social network structure and their consequences onto the individual. In brief, Simmel (1955) describes two types of social forms occurring in premodern and modern eras. First, during the premodern era individuals and their associating groups were geographically and temporally constrained, to such a point "the participation in the smallest of these groups already implies participation in the larger groups" (Simmel 1955:147). The overlaying of institutions situates the individual as well *netted* in society, providing security and support. At the expense of individuality, however, the concentric circles allow little in the way of tolerance and difference, regulating individual's adherence to group values (Pescosolido and Rubin 2000). In modern society the individual, referred to by Simmel as "moral personality" (1955:141), arises from the intersections of multiple groups. Personality is "interpreted as the point of intersection for innumerable social influences" (Simmel 1955:141), where tolerance levels increase, and the networks become of information and choice, not adherence (Pescosolido and Rubin 2000).

Extending from Simmel (1955), Pescosolido and Rubin (2000) discuss the social form of contemporary society. Pescosolido and Rubin (2000) note the nature of relationships in the contemporary era have changed from the long-standing and singular ties of premodern and modern eras to short, functional, and contingent relationships. Arguing contemporary ties produce a new social form, the "spoke" structure (Pescosolido and Rubin 2000), and is defined by four distinct features; (1) individuals are outsiders of their affiliated networks, (2) ties to groups are temporary and multiple, (3) interactions are accomplished through newer modes of media rather than face-to-face communication, and (4) the speed of communication dramatically increases. Individuals are not *netted* within groups, rather they are *strung* together through a series of weak ties, drastically increasing their potential to slip past their social safety net (Pescosolido and Rubin 2000). Individual's agency in spoke networks drastically increase the opportunity to meet others through a series of weak ties (reminiscent of Granovetter's (1977) analysis of weak ties and job opportunities), but the "potential for disenfranchisement" (Pescosolido and Rubin 2000:65) and social isolation is immense. The network typologies described above provide a basis to compare clients' social network types and help to explain possible consequences network types have on client's working alliance with staff members.

2.2 The Network-Episode Model

The study is framed within the Network-Episode Model (NEM) (Pescosolido 1991, 1992, 2006) to analyze clients working alliance with staff members through their personal networks. Underlined by the interactive social process of treatment, "the patterns and pathways of practices and people consulted during an episode of illness" (Pescosolido and Boyer 1999:407) are examined in (e.g., internal ties) and out (e.g., external ties) of the treatment setting. The NEM considers client's "illness career" (Aneshensel 2013), the process of dealing with the initial onset of an illness or routine coping, as influenced by interactions with network members. Depending on the attitudes and beliefs of their network members clients can be driven in and out of care (Pescosolido and Boyer 1999). Building from earlier versions, NEM Phase II (1999) recognizes the ties clients develop with their treatment providers as nested within the "climate of care," playing a significant role in treatment (Pescosolido and Boyer 1999:409). Client's connections with staff members are formal ties because of the explicit role of the staff member to treat in a system of care. Staff members are also internal ties because they reside within the treatment system and are not part of client's external community.

Framed in the context of the NEM, evaluating client's formal internal personal networks are based on two premises; network structure—the arrangement of staff members around the client—and their functions—the kinds of support that staff members supply, be it emotional, social, or treatment support. Staff members could be supportive agents to clients through frequent contact and supplying multiple kinds of support, while others are dismissive of non-illness related aspects of client's life, such as sexual issues and matters of importance. Considering the influence staff members have during treatment, the networks immediately surrounding clients provide insights into the effects of healthcare systems and providers to the client level (Pescosolido 2011; Pavalko, Harding, and Pescosolido 2007).

In the present study, I am first interested in the network types that will be derived from structural and functional features of client's ties with staff members. Investigating if there are specific kinds of support that define network types and, if so, which kinds? Taken together with previous finding from community network types (Fiori et al. 2006, 2007; Litwin 2001; Wegner 1997; Wellman and Potter 1999;), I hypothesize that I will find a supportive network, unsupportive network, and a treatment oriented network among clients with SMI. To empirically test this, I investigate the types of formal internal personal networks based on structural and functional measures and compare them across client level demographics. Next, if network types are derived from structural and functional network measures, what, if any, are the implications of these network types onto client's working alliance? Examining the relationship between network types and clients working alliance could provide insights into possible mechanisms in the treatment process. Therefore, considering earlier research examining network types and client-level outcomes (Chronister et al. 2016; Wright et al. 2006), I hypothesize clients with supportive networks will predict a stronger working alliance with staff members than unsupportive and treatment focused network types. Furthermore, the treatment oriented network will be associated with a weaker working alliance than non-supportive networks. I test this by comparing the network types to client's working alliance for possible associations. Also included are client demographics and variables related to illness to examine possible associations.

3 METHODS

3.1 Data

Data comes from the Indiana Mental Health Services and HIV Risk Study (IMHSHRS), a cross-sectional study collecting data between 2000 and 2001 of clients with SMI receiving treatment (Wright 1999). The study focuses on the sexual lives, sexuality, and client-staff interaction of services related to HIV for clients with SMI. Researchers used surveys and face-to-face interviews to collect data on self-perceptions, attitudes, and treatment culture of both clients and staff members. In this study, I use survey data from client's perceptions of their respective staff members in treatment facilities. The sample includes clients from five treatment locations, three CMHCs and two SPHs in the state of Indiana. Convenience sampling at smaller SPH locations and random sampling with administrative data in the larger CMHCs was used to recruit respondents. Participants had to meet the following eligibility criteria; (1) must have been between 18 to 60 years old at the time of data collection; (2) a diagnosis of an SMI negatively affecting their daily functioning; (3) receiving psychiatric treatment for a minimum of two years; (4) receiving treatment at the specific location for at least 3 months; (5) no criminal charges or in jail at the time of data collection. The participation rate was 74% (N=417) across the five treatment locations.

IMHSHRS network data is uniquely suited to investigate clients formal personal network types because of the available structural and functional measures. The five name generators used to elicit alters and in-depth name interpreters allow me to construct multi-dimensional network types. Few studies collect data on clients with SMI in the treatment system and even less on personal networks of clients informal and formal ties (Pescosolido, Gardner, Lubell 1998). Data used in this analysis allows for an in-depth quantitative examination of client-staff interactions in the treatment system through network specific measures and constructed scales. Furthermore, the IMHSHRS diversifies the network literature to include a population where little is known about client's personal networks in the treatment system and inform network typological research.

The IMHSHRS contains data on the sexual networks and health networks of clients across five treatment locations. This study utilizes the health network data constructed from five name generators to elicit staff members (e.g., alters) from clients (e.g., ego) creating an egocentric network. Included are a modified version of the General Social Survey "important matters" name generator (Marsden 1987) of whom clients talk about important matters with in the last three months, another of emotional and physical health, and discussion of sex or sex-related problems. The fourth and fifth name generators are specific to staff members, which clients discuss important matters, emotional or physical health, and/or sex-related matters with in the last three months and clinicians important to the client's treatment team, respectively. These exchange-based name generators elicit alters supplying various kinds of support, revealing the functional specificity of staff members to the client (Perry et al. 2018). Clients could name the same staff member in multiple name generators allowing to measure the multiplexity—the number of separate ties between two actors—of functional support. Additionally, utilizing five different name generators increases the chance of eliciting a greater number of alters and the various kinds of functional support they provide (Perry et al. 2018). Below interviewers asked clients "Now I'd like you to tell me about the most important people in your life right now. Looking back over the past 3 months"…

1) Who are the people with whom you discussed matters important to you? These can include anyone in your life; family, friends, mental health or other health care professionals, people who live nearby or people who live far away. Who are the people in your life right now who you feel you can talk to or depend on for help if you need it?

2) Who are the people with whom you discussed your emotional and physical health? Who are the people in your life that you feel you can really count on for help when you have emotional or physical health problems?

3) Who are the people you talk about sex or sex-related problems? Remember, these can be anyone in your life including family, friends, and mental health or other healthcare professionals.

4) Who are the staff members here that you talked with about matters that are important to you? Which staff members do you talk with about your emotional and/or physical health, for example? Who do you feel you can depend on here when you want to talk about sex-related matters?

5) Who are the most important members of your treatment team?

Only the client's staff member(s) are included in the analysis and all external ties excluded to focus on the types of personal networks within the treatment system and to test implications onto client's working alliance. Thus, the present study only analyzes the client's formal internal personal network ties within the treatment system.

3.2 Constructs

3.2.1 Independent Variables

Network Types. I dichotomized each identified network type during the clustering analysis into five separate variables. Overall, 1590 alters were nominated from clients (*N*=417) with the majority, 53.5% (n=850) being that of staff members. All clients who did not nominate any staff members are considered isolates and excluded from this analysis. I included two structural and five functional network variables in the cluster analysis to derive network types.

Average frequency of contact with staff members. The first structural variable, frequency of contact, measures the amount of interaction clients have with staff members. Clients' responses to "How often do you see or talk to him/her?", that are staff members; 25.3%

(n= 192) were talked to by clients "Everyday"; 28.1% (n=213) "Several times a week"; 21.2% (n=161) "Several times a month"; 9.88% (n=75) "Once a month"; and 15.6% (n=118) "Less than once a month". Staff members whose clients responded, "Don't know" and "Refused" are coded as missing. I aggregated each response from the alter-level (staff member) to the ego-level (client) by summating each staff member's value and then dividing by the size of the client's network. The variable is coded as the following; 1= "Less than once a month"; 2= "Once a month"; 3= "Several times a month"; 4= "Several times a week"; 5= "Everyday"[1]. Additionally, previous research of community networks types identify frequency of contact with alters as an important factor in deriving network typologies (Fiori et al. 2006; Wenger 1997; Wellman and Potter 1999).

Average perceived multiplexity of staff members. The second structural variable, multiplexity of support, measures the different kinds of support staff members supply. I totaled the number of occurrences each staff member was nominated in all five name generators. That is, a staff member nominated in the first and third name generators is perceived to supply both "important matters" and sexual support and would be receive a multiplexity score of two. All five name generators are equally weighted. I aggregated each response from the alter-level to the ego-level by summating each staff member's multiplexity score and dividing by the network size. The majority (54.7%, n=415) of staff members are perceived to supply one type of support and only 1.9% (n=14) are perceived to supply no support to clients. 9.8% (n=150) of staff

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[1] The IMHSHRS contains other structural measures including how long the client has known each staff member (scale from 1 = "Less Than 6 Month" to 5 = "More than 6 Years") and how close the client feels to each staff member (1 = "Very close" to 3 = "Not very close"). Both have a high amount of missing data and are not included in the cluster analysis to preserve sample size.

members are perceived to supply two kinds of support; 10.8% (n=82) are perceived to supply three kinds of support; 6.7% (n=51) are perceived to supply four kinds of support; and 6.2% (n=47) are perceived to supply five kinds of support.

Ratio of perceived support. The five functional variables measure the perceived number of staff member(s) supplying a certain kind of support in a client's network. By using the exchange-based name generators as the indicator, I calculated the ratios for each kind of support in a network; (1) "important matters", (2) emotional and physical health, (3) sex or sex-related support, (4) general staff support, and (5) treatment team. I aggregated these variables from the alter-level to the ego-level by summating the number of staff member(s) elicited in each name generator and divided by the network size. A proportional variable was created for each name generator, ranging from 0 to 1. 0 indicates no staff member(s) was perceived to supply a particular kind of support to the client and 1 indicating every staff member in the network was perceived to supply that particular kind of support. During data collection the strength or frequency of support staff members supplied was not collected, thus only presence or absence of each staff member to supply support is measured.

3.2.2 Dependent Variable

Working alliance. I operationalize client-staff interaction using the Working Alliance Inventory short form scale (WAI-S) (Tracey and Kokotovic 1989). The WAI-S is the most widely used scale to evaluate working alliance during treatment. Clients were asked about their perceived collaborative relationship of nominated staff members in their network with a twelve-item questionnaire. The scale measures client perception in the consensus of treatment goals, agreement that treatment will improve the client's situation, and the quality of the bond between client and staff member (Horvath and Symonds 1991).

Questionnaire items measure client's perception of the staff member to agree, support, believe, feel confident in, and trust one another to improve the situation as an indicator of good working alliance. Item options range from 1 = "Not at all true", 2 = "Slightly true", 3 = "Somewhat true", 4 = "Fairly true", and 5 = "Very true". The options "Don't Know" and "Refused" are recoded as missing. Additionally, items "(NAME) does not understand what I am trying to accomplish in treatment." and "(NAME) and I have different ideas about what my problems are." are reversed coded to match the direction of other items. Confirmatory factor analysis indicates good model fit after the item "(NAME) and I have different ideas about what my problems are." was excluded (χ^2(44)= 268.729***, CFI= 0.997, TLI=0.996, and RMESA= 0.043)[2]. Across earlier studies, inconsistencies in WAI-S factor loading have found one (Tracey and Kokotovic 1989) and two factors (Andrusyna et al. 2001) in the scale and even determined the excluded item, "(NAME) and I have different ideas about what my problems are.", as problematic (Hatcher and Gillaspy 2006). Thus, I precede with the eleven remaining items that are summated together to form a complete scale ranging from 11 indicating poor perceived working alliance with staff member to 55 a strong perceived working alliance with staff members (α = 0.90)[3]. To test the association with network types, the working alliance is also aggregated from the alter-level to the ego-level by averaging the summated scores of each staff member in a client's network. Therefore, I am able to test the implications of clients' network types on their working alliance.

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[2] Confirmatory factor analysis was conducted using the "lavaan" (Rosseel 2012) package in R. Since all the scale items are measured at the ordinal level and missing data is present, robust diagonally weighted least squares estimator was used to determine model fit.

[3] This is the averaged α score from the twenty imputations of the remaining eleven questionnaire items.

To preserve sample size for analyses, twenty multiple imputations with thirty iterations each was conducted for the eleven items[4] [5]. Table 1 below shows the original questionnaire items of the WAI-S scale.

[4] Little's missing completely at random (MCAR) test indicated the data is missing completely at random (p = .752). Imputations were conducted using the "mice" (Groothuis-Oudshoorn and Buuren 2011) package in R. Since all the scale items are measured at the ordinal level, proportional odds logistic regression ("polr") model was used. Convergence was achieved for all imputations.

[5] Each item of the scale for each staff member was imputed, then summated, and finally aggregated to the client-level. This was done to improve precision of the imputed items.

Table 1. Working Alliance Inventory short form scale (WAI-S)

	Questionnaire items	Options	Transformations
1.	(**NAME**) and I agree about the kinds of things I will need to do in treatment.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
2.	I believe (**NAME**) likes me.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
3.	(**NAME**) does not understand what I am trying to accomplish in treatment.	1 = Very true 2 = Fairly true 3 = Somewhat true 4 = Slightly true 5 = Not at all true	Reverse coded
4.	I am confident in (**NAME**)'s ability to help me.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
5.	(**NAME**) and I are working toward mutually agreed upon goals.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
6.	I feel that (**NAME**) appreciates me.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
7.	(**NAME**) and I agree on what is important for me to work on.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None

8.	I believe the way (**NAME**) and I are working with my problems is correct.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
9.	(**NAME**) and I trust one another.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
10.	*(**NAME**) and I have different ideas about what my problems are.	1 = Very true 2 = Fairly true 3 = Somewhat true 4 = Slightly true 5 = Very true	Reverse coded
11.	(**NAME**) and I have established a good understanding of the kinds of changes that would be good for me.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None
12.	What (**NAME**) and I are doing in treatment gives me new ways of looking at my problems.	1 = Not at all true 2 = Slightly true 3 = Somewhat true 4 = Fairly true 5 = Very true	None

*excluded from scale due to poor model fit indicated by confirmatory factor analysis
Cronbach's alpha (11 remaining items)= 0.90
Confirmatory factor analysis (11 remaining items): $\chi^2(44)$= 268.729***, CFI= 0.997, TLI=0.996, and RMESA= 0.043

3.2.3 Control variables

Gender. The sociodemographic covariate gender is a control variable in the regression analysis. The majority of clients, 57.93% (n=190) identify as "Male" and 42.07% (n=138) identify as "Female". Gender categories are dichotomized, 0 = "Man" and 1 = "Woman".

Race. The sociodemographic covariate race is a control variable in the regression analysis. The majority of clients, 67.68% (n=222) identify as "White"; 26.83% (n=88) "African

American”; 0.92% (n=3) “Asian”; 0.61% (n=2) “Hispanic”; and 3.96% (n=13) “Other”. Due to low responses in certain categories, I collapsed race into a dichotomous variable 0 = “White” and 1 = “Non-White”.

Age. The sociodemographic covariate age is a control variable in the regression analysis. Client’s age at the time of data collection was measured in years. Age was calculated by subtracting the date of the interview from the client’s answer to “What is your birth date?”. Age of clients range from 18-56 years.

Education. The sociodemographic covariate education is a control variable in the regression analysis. Clients answered, “What degrees or certifications have you earned, if any?”, the majority 49.70% (n=163) have a “H.S. Diploma/GED”; 6.10% (n=20) “Vocational certification”; 4.88% (n=16) “Associates Degree (2- year college)”; 4.27% (n=14) “College Degree (BA, BS)”; 1.22% (n=4) “Masters degree or equivalent (MA, RN)”; 0.30% (n=1) “PhD”; 0.30% (n=1) “MD or DDS”; and 33.23% (n=109) do not have any educational degree. Due to low response rates in certain categories, I recoded this variable as 0 = “No educational degree”; 1 = “H.S. Diploma/GED”; 2 = “Vocational certificate and higher”.

Marital status. The sociodemographic covariate marital status is a control variable in the regression analysis. Clients’ responses to “What is your marital status?” are 10.98% (n= 36) indicated they are 1= “Currently Married or Cohabitating”; 26.22% (n=86) are 2= “Divorced/Separated or Widowed”; and 62.80% (n=206) have 3= “Never married”.

Work Status. The sociodemographic covariate work status is a control variable in the regression analysis. Clients were asked: “Are you Currently Working?” The majority 84.15% (n=276) report that they are “Not Currently Working” and 17.07% (n=56) are “Currently Working”. The variable is coded as 0=“Not Currently Working” and 1=“Currently Working”.

Diagnoses. The diagnosis variables related to illness are control variables in the regression analysis. Clients diagnosed with schizophrenia, major depression, bipolar disorder, and another major disorder are coded into four different dichotomous variables. 0= "No diagnosis of schizophrenia" and 1= "Diagnosis of schizophrenia"; 0= "No diagnosis of major depression" and 1= "Diagnosis of major depression"; 0= "No diagnosis of bipolar disorder" and 1= "Diagnosis of bipolar disorder"; and 0= "No diagnosis of other major disorder" and 1= "Diagnosis of other major disorder". 50.00% (n=164) clients were diagnosed with schizophrenia; 10.98% (n=36) clients were diagnosed with major depression; 7.62% (n=25) clients were diagnosed with bipolar disorder; and 31.40% (n=103) clients were diagnosed with another major disorder.

Level of Functioning. The variable related to illness, level of functioning, is a control variable in the regression analysis. The client's level of functioning is measured using the Global Assessment of Function (GAF) score (Jones et al. 1995). The scale ranges from 10- "Persistent danger of severely hurting self or others (e.g., recurrent violence) or persistent inability to maintain minimal personal hygiene or serious suicidal act with clear expectation of death." to 100- "Superior functioning in a wide range of activities, life's problems never seem to get out of hand, is sought out by others because of his or her many positive qualities. No symptoms."

Length of psychiatric symptoms. The variable related to illness, length of psychiatric symptoms, is a control variable in the regression analysis. This indicates the length of time clients have displayed psychiatric symptoms. I calculated this variable by subtracting the clients age by the age they first are known to have displayed psychiatric symptoms. Clients range from 1-45 years in the length of psychiatric symptoms. Since the data used in this analysis is cross-sectional, measuring network dynamics is impossible, I control for the length of time clients have displayed symptoms as an indicator of how long they have been in their illness career.

Treatment facility. The variable related to illness, treatment facility, is a control variable in the regression analysis. At the time of data collection, client's treatment location was coded as 0 = "community mental health center" and 1= "state psychiatric hospital". 53.7% (n=176) clients are in a community mental health center and 46.3% (n=152) in a state psychiatric hospital. Descriptive statistics of each variable are included in Table 2. below.

3.3 Statistical Analysis

This study utilizes k-means clustering and weighted least squares regression to examine client's formal personal networks and the association to their working alliance in R version 3.6.1 (R Core Team 2019). First, k-means clustering analysis identifies five network types. I investigate the structural and functional features to reveal client network typologies in the treatment system. Second, I examine the association between network types and clients working alliance using weighted least squares regression, testing for possible mechanisms.

3.3.1 Clustering Analysis

I use k-means clustering (Hartigan and Wong 1979) to derive network types. K-means clustering in an unsupervised exploratory clustering technique that reveals distinct and unique grouping of the formal personal networks of clients. Clustering analysis partitions observations based on a series of predetermined variables into classifications of similar groupings, while also maximizing differences between groupings (Hamerly and Drake 2015; Kassambara 2017). To optimize clustering, the k-means algorithm is agglomerative, that is adding observations after each phase of the analysis, and iterative, conducting the process over again until convergence is achieved (Meyers, Gamst, and Guarino 2016). Assigning observations to clusters multiple times throughout the process determines the best clusters to minimize inter-cluster variation and maximize intra-cluster variation (Kassambara 2017). K-means clustering examines the groupings of seven client network variables: average frequency of contact; average perceived multiplexity; ratio of perceived "important matters" support; ratio of perceived health support; ratio of perceived sexual support; ratio of perceived general staff support; ratio of perceived treatment team support[6]. The selection of these variables utilizes the NEM's network measures for client's personal networks to reveal five distinct formal personal networks.

My study uses the Hartigan and Wong (1979) k-means algorithm for clustering analysis. The expressed function is:

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

where *k* represents the number of clusters pre-specified by the researcher. x_i is a datum point in the cluster C_k and μ_k is the mean of data points in the same cluster. The algorithm minimizes within-cluster sum of squares (WCSS) (e.g., 'compactness') while also maximizing between-cluster sum of squares (BCSS) (e.g., 'distinctness'), by positioning 'centers' at optimal distances from data points (Hamerly and Drake 2015; Kassambara 2017; Wu 2012). I use Euclidian distance as the measure between the seven network variables for this analysis. Euclidian distance is best for measuring the graphical distance between observations with a large range in values (Kassambara 2017), such occurring relative to the seven network variables. All variables are standardized to z-scores to make distances between observations comparable. Thus,

[6] K-means clustering is sensitive to the order of the specified variables. The order of the variables during analysis is as presented here. This is also the order that the name generators appear in the survey instrument.

clients with similar levels of perceived network characteristics of staff members are grouped together to form a unique and distinct cluster.

Before the clustering analysis, I assess the clustering tendency of the seven network variables to determine if naturally occurring clusters exist. The Hopkins statistic tests the likelihood the observed data's distribution is similar to a randomly generated dataset with uniform distribution (Hopkins and Skellam 1954). A value below 0.5 indicates a high probability that naturally occurring clusters are present in the observed data (1954). Next, I conduct a visual assessment of cluster tendency (VAT) to test if cluster structures are present with a heat map of the proportion dissimilarity among observations (Bezdek and Hathaway 2002).

K-means clustering does have limitations when clustering real world data. Where *k* is determined by the researcher and must be informed by theory and tests. Regardless of the number of clusters set, the algorithm will cluster the data even when no naturally occurring cluster tendencies exist (i.e., uniform distribution) (Kassambara 2017). The k-means algorithm is also sensitive to outliers that may cause inaccurate groupings of observations since centroids are randomly assigned[7] (Wu 2012). This is mitigated by performing many iterations, allowing the algorithm greater opportunity to randomly position centroids for optimal distance between points[8] (Wu 2012). Additionally, the type of distance measurement selected across parameters

[7] Outliers were identified in the analyzed data and may have led to inaccurate groupings of some observations. For further methodological robustness, I conducted partition around medoids (PAM) clustering that yielded similar clustering and regression results. PAM clustering is a robust variation of k-means clustering that is less susceptible to outliers (Kassambara 2017). I only the report k-means clustering results because of acceptable goodness-of-fit of the model and to be easily comparable with results in the literature.

[8] 1000 iterations were performed with 50 initial configurations for centroids.

will yield different results and must be appropriate for the data. Still, k-means clustering is one of the most widely used and reliable clustering algorithms available (Hamerly and Drake 2015; Kassambara 2017; Meyers et al. 2016; Wu 2012) and appropriate for this analysis.

Since the optimal *k* clusters for k-means clustering must be determined beforehand, I use the Elbow method[9] (Ketchen and Shook 1996), Silhouette method[10] (Rousseeuw and Kaufman 1990), and Gap statistic[11] (Tibshirani, Walther, and Hastie 2001) as indicators. The silhouette coefficient[12] (Rousseeuw and Kaufman 1990), Dunn index[13] (Dunn 1974), and proportion of variance explained (often referred to as the 'k-means score')[14] are used as internal cluster validation measures to evaluate the clustering results. A silhouette coefficient value close to one, a low WCSS value (for the Dun index), and high proportion of variance explained when compared to other *k* clusters indicate goodness-of-fit of clusters (for the k-means score)

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[9] The Elbow method plots the WCSS by the number of clusters. This indicates the compactness of the clusters as a function of the number of clusters.

[10] The Silhouette method plots the quality of clustering as the 'wellness' of each observation in the assigned cluster.

[11] The Gap statistic determines *k* by comparing the WCSS variation to a randomly generated dataset with uniform distribution to find the greatest 'gap' between the two datasets.

[12] The silhouette coefficient measures how similar an observation is to its assigned cluster when compared to other clusters. The measure ranges from -1 to +1.

[13] The Dunn index measures of the 'compactness' of clusters as an indicator for how well the algorithm assigned observations to groupings. The closer the value is to zero the better 'compactness' of clusters. The measure ranges from 0 to 1.

[14] The 'k- means score' is calculated by dividing the BCSS and TCSS (total-cluster sum of squares. The measure is reported as a percentage of explained variance.

(Kassambara 2017; Wu 2012). Cases with missing data in the seven parameters are removed using listwise deletion, resulting in a clustering analyzed sample of 328 clients[15].

3.3.2 Regression Analysis

Weighted Least Squares (WLS) regression tests the direct association of client's network types and demographics onto client's working alliance. Forward stepwise WLS regression is appropriate to test changes in the mean of a scale dependent variable according to multiple predictor values in the model (Fahrmeir et al. 2013). When the variances of residuals are not constant and heteroscedastity is detected, ordinal least squared regression (OLS) no longer provides the best linear unbiased estimate (BLUE) (Gill and Torres 2019). To mitigate the effect of unequal variances on estimates, weights are applied to the errors of variance in the model (Gill and Torres 2019). Observations with little variance are weighted more than those with greater variance by multiplying the inverse of the observation's calculated weight[16]. In this study, the working alliance is a continuous scale variable tested against categorical and continuous independent variables. The equation is:

$$\Omega^{-1}Y_i = \alpha + \Omega^{-1}\beta_1 x_1 + \Omega^{-1}\beta_2 x_2 \ldots + \Omega^{-1}\beta_k x_k + \Omega^{-1}\varepsilon$$

where Ω^{-1} is the inverse of the diagonal matrix weight applied in the model of Y_i the working alliance, α is the Y_i-intercept, and $\Omega^{-1}\beta$ is the regression coefficient slope for the value of *x* with its specific weight applied, an independent variable. However, limitations of WLS

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[15] The k-means algorithm requires there is no missing data among the seven network variables. Listwise deletion was used to remove observations with missing values.

[16] Weights were calculated by the inverse of the predicted values from OLS regression.

regression exist. By assuming linearity, only the direct relationship between the working alliance and network types are tested, thus WLS is not able to show indirect pathways between variables (Agresti and Finlay 2009). WLS is also sensitive to outliers, removing clients whose values have high leverage, which affect coefficient estimates, loses valuable cases[17] (Agresti and Finlay 2009). Finally, the reported range of clients working alliance also changes the explained variance of the model, resulting in a possible underestimation of correlations (Agresti and Finlay 2009). Using listwise deletion, my final regression analyzed sample includes 248 clients.

Model 1 tests the relationship between the NEM's "Episode Base" (Pescosolido 1992) control variables and the working alliance. These include sociodemographic variables and variables related to client's illness. Model 2 includes the five network types to test the relationship between structural and functional network measures on the working alliance.

[17] Some observations were identified as high leverage cases and excluded from the regression analysis.

4 RESULTS

4.1 Descriptives

Summary statistics for all study variables are presented in Table 2. below. Men (57.93%) are the majority and the mean age is 39.31 years old in the sample. 67.68% of clients are white. Nearly half of clients (49.70%) have a high school diploma or a GED, the next largest group is clients with no educational degree (33.23%), leaving 17.07% with a vocational certificate and higher. The majority of clients have never been married (62.80%), next most frequent are clients divorced/separated or widowed (26.22%), with 10.98% as married or cohabitating. Most clients are not working (84.15%). Clients diagnoses consisted of half (50.00%) as schizophrenic, 10.98% diagnosed with major depression disorder, 7.62% diagnosed with bipolar disorder, and 31.40% diagnosed with another major mental health disorder. Clients average level of functioning is 47.01 and average length of psychiatric symptoms is 17.97 years. Clients average working alliance score is 44.52.

Table 2. Summary Statistics of Study Variables

		%(N)		
		Treatment Location		
		CMHC (n=176)	SPH (n=152)	Total (n=328)
Dependent variable				
Working alliance		46.41(8.55)[a]	42.31(9.82)[a]	44.52(9.37)[a]
Network types				
Supportive context		10.80(19)	3.95(6)	7.62(25)
Sparse context		18.18(32)	17.11(26)	17.68(58)
Diverse context		12.50(22)	13.16(20)	13.41(44)
Clinical context		33.52(59)	25.66(39)	29.88(98)
Treatment-focused context		25.00(44)	40.13(61)	32.01(105)
Client demographics				
Gender				
	Men	50.57(86)	68.42(104)	57.93(190)
	Women	51.14(90)	31.58(48)	42.07(138)
Race				
	Not white	35.80(63)	28.29(43)	32.32(106)
	White	64.20(113)	71.71(109)	67.68(222)
Age[b]		41.67(8.69)[a]	36.59(10.26)[a]	39.31(9.77)[a]
Education				
	No educational degree	31.25(55)	35.53(54)	33.23(109)
	H.S. Diploma/GED	47.73(84)	51.97(79)	49.70(163)
	Vocational certificate and higher	21.02(37)	12.5(19)	17.07(56)
Marital status				
	Married or Cohabitating	16.48(29)	4.61(7)	10.98(36)
	Divorced/ Separated or Widowed	29.55(52)	21.05(32)	26.22(86)
	Never Married	52.84(93)	87.50(113)	62.80(206)
Work status				
	Not currently working	80.11(141)	86.18(135)	84.15(276)
	Currently working	19.89(35)	13.82(21)	17.07(56)

Variables related to illness				
Schizophrenia				
	No	50.57(89)	49.34(75)	50.00(164)
	Yes	49.43(87)	50.66(77)	50.00(164)
Major depression				
	No	85.23(150)	93.42(142)	81.71(268)
	Yes	14.77(26)	6.58(10)	10.98(36)
Bipolar disorder				
	No	90.34(159)	92.31(144)	92.38(303)
	Yes	9.66(17)	5.26(8)	7.62(25)
Other major disorder				
	No	73.86(130)	62.50(95)	68.60(225)
	Yes	26.14(46)	37.50(57)	31.40(103)
Level of Functioning		53.48(13.08)[a]	39.51(12.41)[a]	47.01(14.54)[a]
Length of psychiatric symptoms		18.11(10.34)[a]	17.85(10.28)[a]	17.97(10.29)[a]

N=328
[a] $\bar{x}(\sigma)$
[b] Years (Range=18-55)
[d] Years (Range=1-45)

4.2 Clustering Analysis

Table 3. shows the results from the clustering analysis. Results from the Hopkins statistic (H=0.3) indicate the data is not uniformly distributed and the VAT test show low dissimilarity among the seven variables; demonstrating the data is appropriate for clustering. The Elbow method and Silhouette method indicate a k of two as the optimal number for clusters, while the Gap statistic suggests nine. After testing various numbers of k clusters to “partly construct” and “partly discover” (Stone and Rosenthal 1996) client’s network types, I determined that five clusters as the most theoretically meaningful with the best relative model fit. A Silhouette coefficient (S_i= 0.3), Dunn index (DI_m= 0.12), and proportion of explained variance (BCSS/TCSS= 73.7%) indicate acceptable goodness-of-fit of the model.

Five distinct network types are revealed; *supportive context*, *sparse context*, *diverse context*, *clinical context*, and *treatment-focused context*. I ran bivariate associations (chi-squared and ANOVA) of network types across clustering variables and client demographics as another test of validity (Fiori et al. 2007). Overall, network types differed significantly by clustering variables except for frequency of contact where all network types are not significantly different from each other. Additionally, clients with sparse context and clinical context have the greatest number of variables that are not statistically different between each other. Demographic characteristics are significantly different by gender, education (p < 0.1), level of functioning, treatment location, and network size.

Cluster one (n=25), *supportive context* is the most resourceful network type. Clients in this cluster perceive the highest percentage of staff member(s) supplying "important matters" support (91%), health support (99%), sexual support (100%), general staff support (92%), and treatment support (93%). The average perceived multiplexity of staff member(s) ($\bar{x}$ =4.75) and the reported frequency of contact with staff member(s) ($\bar{x}$ =3.57) are the highest among any cluster. Clients in a supportive context also average the smallest network size ($\bar{x}$ =1.88), significantly smaller than clinical contexts. Most clients in a supportive context are women (72%) and 76% receive treatment in a CMHC, the highest percentage of any cluster.

Cluster two (n=58), *sparse context*, is distinctly different from the previous cluster. Staff member(s) supplying "important matters" support (30%), health support (31%), sexual support (4%), general staff support (41%), and treatment support (5%) are significantly lower than supportive contexts. Staff members, on average, are reported to supply only one kind of support ($\bar{x}$ =1.11), significantly less than supportive context, diverse context, and clinical context. Clients also have marginally less frequent contact with staff members ($\bar{x}$ =3.10) compared to diverse context. Average network size ($\bar{x}$ =1.97) is significantly smaller than clinical context and majority of client's gender shifts to men (53%). An increase in the percentage of clients receiving treatment in SPH to 45%. Interestingly, clients' level of functioning is significantly greater compared to clients with treatment-focused contexts.

Cluster three (n=42) is deemed *diverse context*. Clients report the lowest average frequency of contact with staff members ($\bar{x}$ =2.97) and the second highest average multiplexity ($\bar{x}$ =3.21). The percentages of health support (74%), sexual support (27%), general staff support (66%), and treatment support (74%) are significantly lower than supportive contexts, except for "important matters" (81%). This suggests clients in a supportive context and diverse context view their staff members as close confidants. The majority of clients in diverse context are women (55%) and the average network size is significantly smaller than clinical context ($\bar{x}$=2.12). 48% of clients are receiving treatment in a SPH.

Cluster four (n=98), *clinical context*, is characteristic of higher functional specificity by moderate to low perceived "important matters" support (19%), health support (20%), and sexual support (8%). High perceived general staff support (71%), and treatment support (68%) is significantly different than supportive context, diverse context, and treatment-focused context. Clients average contact with staff members ($\bar{x}$ =3.31) and average perceived multiplexity ($\bar{x}$ =1.87) is significantly higher than of treatment-focused context. 43% of clients in this cluster are women and 40% are receiving care in a SPH. Clients with clinical contexts have a significantly higher level of functioning compared to treatment-focused contexts.

Cluster five (n=105), *treatment-focused context*, is defined as the most functionally specific with high perceived treatment support (90%) and very low "important matters" support (4%), health support (4%), sexual support (1%), and general staff support (8%). Consequentially, staff member(s), on average, are perceived to supply only one kind of support ($\bar{x}$ =1.06). Clients in treatment-focused context contact staff ($\bar{x}$ =3.19) marginally less than clinical context. More clients (58%) in this cluster receive treatment at SPHs compared to all other clusters. Table 3. presents the means and the bivariate associations from the clustering analysis. Table 4. presents sociodemographic means and bivariate associations between network types. Figure 1. displays the levels of support in each network type based on the five name generators.

Table 3. Group Means and Proportions of Structural and Functional Network Variables by Social Network Types

Variables	*Network Types* Supportive context (n = 25)	Sparse context (n = 58)	Diverse context (n = 42)	Clinical context (n = 98)	Treatment-focused context (n = 105)	*F*(*df*)
	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\bar{x}$	
"Important matters" support	0.91_{a}	0.30_{b}	0.81_{a}	0.19_{b}	0.04	$F(4)=94.75$***
Health support	0.99	0.31_{a}	0.74	0.20_{a}	0.04	$F(4)=103.96$***
Sexual support	1.00	$0.04_{a, b}$	0.27	0.08_{a}	0.01_{b}	$F(4)=181.11$***
General staff support	0.92	0.41	0.66_{a}	0.71_{a}	0.08	$F(4)=66.18$***
Treatment team support	0.93_{a}	0.05	0.74_{b}	0.68_{b}	0.90_{a}	$F(4)=122.47$***
Multiplexity of support	4.75	1.11_{a}	3.21	1.87	1.06_{a}	$F(4)=557.95$***
Frequency of contact	$3.57_{a, b, c, d, e}$	$3.10_{a, b, c, d, e}$	$2.97_{a, b, c, d, e}$	$3.31_{a, b, c, d, e}$	$3.19_{a, b, c, d, e}$	$F(4)=1.21$

Notes: N=328
Results of Tukey post hoc test are indicated by matching subscripts, where means in the same row do no differ at the $p<0.05$ or lower.
Variables range as follows: "Important matters" support 0-1; Health support 0-1; Sex support 0-1; Staff support 0-1; Treatment Team support 0-1; Multiplexity of support 0-5; Frequency of contact 1-5 (1 is contact "Less than one a month" to 5 is "Everyday").
***$p<0.001$.

Table 4. Network Types by Client Demographics

Variables	*Network Types* Supportive context	Sparse context	Diverse context	Clinical context	Treatment-focused context	Statistic(*df*)
Client demographics						
Woman	0.72	0.47	0.55	0.43	0.27	$\chi^2(4)= 22.69$***
White	0.68	0.66	0.67	0.69	0.68	$\chi^2(4)= 0.28$
Age	40.96	41.31	40.79	38.13	38.32	$F(4)=1.66$
Education	0.80	0.72	0.86	1.00	0.75	$\chi^2(8)=12.12$†
Marital status	2.52	2.41	2.48	2.51	2.60	$\chi^2(8)=10.91$
Employed	0.16	0.17	0.29	0.14	0.15	$\chi^2(4)=4.73$
Variables related to illness						
Schizophrenia	0.32	0.43	0.50	0.52	0.56	$\chi^2(4)=6.12$
Major depression	0.16	0.09	0.17	0.13	0.07	$\chi^2(4)=4.89$
Bipolar disorder	0.08	0.10	0.12	0.04	0.08	$\chi^2(4)=3.45$
Other major disorder	0.44	0.38	0.21	0.31	0.30	$\chi^2(4)=5.13$
Level of functioning	47.60	49.59_{a}	48.45	50.57_{b}	$41.53_{a, b}$	$F(4)=6.13$***
Length of psychiatric symptoms	21.00	17.77	19.46	17.05	17.53	$F(4)=0.75$
State psychiatric hospital	0.24	0.45	0.48	0.40	0.58	$\chi^2(4)=12.62$*
Network size[a]	1.88_{a}	1.97_{b}	2.12_{c}	$2.79_{a, b, c, d}$	2.25_{d}	$F(4)=5.09$**
Working Alliance	48.38_{a}	45.25_{b}	46.72_{c}	46.20_{d}	$40.82_{a,b,c,d}$	$F(4)=7.067$***

Notes: N=248
Results of Tukey post hoc test are indicated by matching subscripts, where means in the same row differ at the p<0.05 or lower.
[a]Not included in regression analysis
†p < 0.1. *p<0.05. **p<0.01. ***p<0.001.

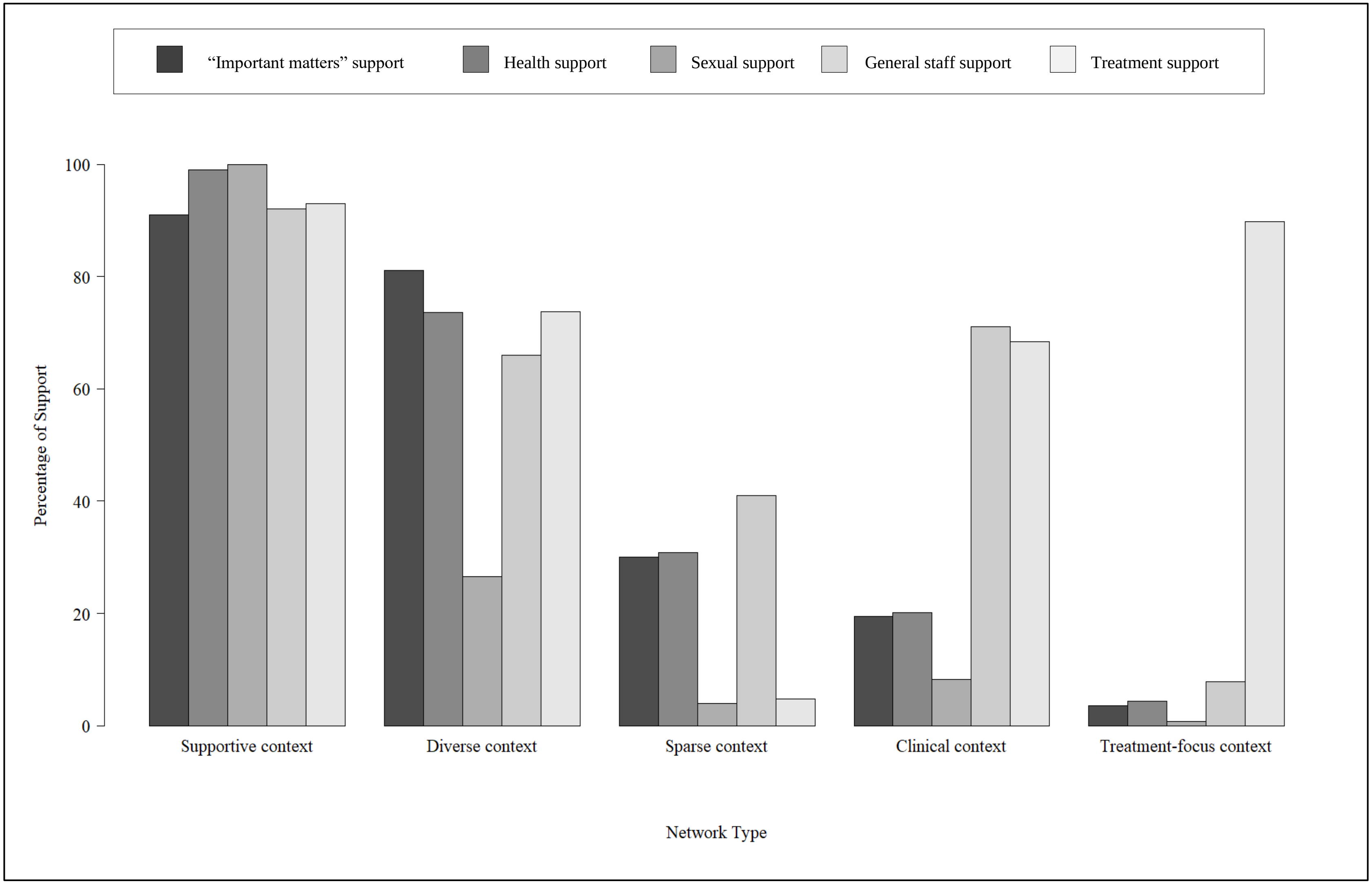

Figure 1. Mean percentages of support of the five name generators by network type.

4.3 Regression Analysis

Table 5. presents the results from Models 1 and 2 where demographics and network types are regressed onto clients' working alliance. Model 1 shows the effects of sociodemographic variables and variables related to illness on clients' working alliance. Clients with a high school diploma/GED or a vocational certificate and higher, on average, are significantly associated with a lower perceived working alliance than clients with no educational degree (β = -1.270, $p \leq .10$), when holding all other variables constant. Although, education's effect is marginally significant. All else held constant, working clients, on average, have a stronger working alliance than non-working clients (β = 2.567, $p \leq .05$). For every one unit increase in clients' level of functioning their working alliance strengthens (β = 0.118, $p \leq .01$), when holding all other variables constant. Clients receiving treatment at SPHs are, on average, marginally associated with a lower working alliance than those in CMHCs (β = -2.186, $p \leq .10$), when all else is constant. While gender varies significantly across network types, results indicate it does not for clients' working alliance.

Model 2 includes the effects of network types with demographic controls on working alliance when treatment-focused context is the reference group. Findings from this model indicate that clients' network contexts are associated with their working alliance. Specifically, clients in a supportive context are associated with the largest average increase of their working alliance (β = 6.257, $p \leq .01$), when holding all other variables constant. The findings show clients with formal internal network ties that are multiplex, perceive a broad range of support and a high percentage of each kind of support, on average, have a stronger working alliance. Interestingly, diverse context (β = 5.696, $p \leq .001$) and clinical context (β = 5.416, $p \leq .001$) average effect sizes are nearly identical, when all else is held constant. This may be because both contexts' levels of general staff support and treatment team support do not significantly differ, indicating the importance of these two kinds of support to clients' working alliance. Sparse context networks have the smallest average effect ($\beta = 4.189$, $p \leq .01$), when holding all other variables constant. Clients' level of functioning becomes less significant to the $p \leq .05$ ($\beta = 0.096$). Likewise, when level of functioning is removed from the model (not shown, available upon request) treatment location becomes significant at the $p \leq .05$ level, indicating treatment location is significantly associated, but client's level of functioning has a greater effect. Clients' education, work status, and treatment location significance levels and average effect sizes do not notably change $p \leq .10$ ($\beta = -1.371$), $p \leq .05$ level ($\beta = 2.716$), and $p \leq .10$ ($\beta = -2.312$) respectively, when holding all other variables constant. Model 2 explains 23.8% of the variance, an increase of 8.5% from Model 1.

Table 5. Weighted least squares regression for network types on working alliance

	Model 1		Model 2	
Network types				
(reference group: treatment-focused context)				
Supportive context			6.257	**
			(1.960)	
Sparse context			4.189	**
			(1.467)	
Diverse context			5.696	***
			(1.559)	
Clinical context			5.416	***
			(1.400)	
Client demographics				
Woman	1.441		0.808	
	(1.131)		(1.056)	
White	1.293		0.986	
	(1.153)		(1.091)	
Age	-0.054		0.003	
	(0.068)		(0.066)	
Education	-1.270	†	-1.371	†
	(0.761)		(0.719)	
Marital status	0.344		0.614	
	(0.767)		(0.698)	
Employed	2.567	*	2.716	*
	(1.252)		(1.153)	
Variables related to illness[b]				
Schizophrenia	-1.169		-1.696	
	(1.227)		(1.170)	
Major depression	0.439		-1.188	
	(1.634)		(1.633)	
Bipolar disorder	-0.726		-0.699	
	(1.946)		(1.722)	
Level of functioning	0.118	**	0.096	*
	(0.041)		(0.039)	
Length of psychiatric symptoms	-0.052		-0.086	
	(0.066)		(0.062)	
State psychiatric hospital (reference group: community mental health center)	-2.186 (1.260)	†	-2.312 (1.172)	†
Constant	41.928	***	38.286	***
	(4.445)		(4.225)	
R^2	0.153		0.238	
F	4.728	***	5.825	***

N=248
[b]Reference group: Other major disorder
Note: Unstandardized beta coefficient are in each cell and standard errors are in parentheses.
†*p* < 0.1. **p*<0.05. ***p*<0.01. ****p*<0.001.

5 DISCUSSION

In this study, I investigated client's network types and the association to their working alliance. The typological approach offers a unique method to derive micro-cultural contexts from structural and functional features of client's formal internal personal networks. My analysis can be used to generalize the finding to clients with SMI in various treatment settings (i.e. CMHC and SPH) and to groups experiencing illness. By using a client-centered typological approach, I am able to examine the multidimensionality of network structure and function in clients' personal networks. Instead of separating the elements of networks, like in variable centered research (Cornwell et al. 2009; Perry and Pescosolido 2010, 2015), the clustering method considers the network as the unit of analysis. Providing a theoretical foundation for interpreting client's micro-cultural contexts and the implications of contexts onto client's working alliance with staff members.

5.1 Personal Network Contexts and Working Alliance

Partially supporting hypothesis one, I found two supportive network types, supportive context and diverse context. Clients in these network types perceive their staff members to supply a broad range and high level of support (see Figure 1.). In addition, a non-supportive network type, sparse context, was revealed where clients perceived staff members to supply little to no support (see Figure 1.). I also found two different types of treatment oriented networks, clinical contexts, characterized by high levels of general staff support and treatment support with low levels of "important matters" support, health support, and sexual support. And treatment-focused context, characterized by similarly low levels of "important matters" support, health support, and sexual support, but a high percentage of treatment team support with consequentially the lowest average multiplexity.

I use cross-sectional data as a snapshot to investigate client's formal internal personal network types and their consequences onto the client, which mirrors the approach of Simmel (1955) and Pescosolido and Rubin (2000). Earlier research on social support and network types have focused on external community ties (Bellotti 2008; Chronister et al. 2016; Fiori et al. 2006, 2007; Litwin 2001; Wegner 1997; Wellman and Potter 1999), making comparison difficult to the study's results. Clients in the supportive context are the most functionally broad and perceive the highest amount of support of any network type. Coupled with an elevated level of averaged network multiplexity, clients perceived staff members supplying extensive support. I can conceptualize each structural and functional measure as a string in a net, where clients in a supportive context are well *netted* in the treatment system. Following this analysis and results, I find that staff members may yield considerable social influence on clients and as a result are more prone to embrace optimism towards treatment, improving outcomes.

Hypothesis two is supported. My results from the regression analysis significantly indicate that supportive contexts predict the strongest working alliance compared to clients with other network types. Following intuition, clients that perceive staff members as supportive across a range of issues view their relationship with staff as more trusting. My findings align with Perry and Pescosolido's (2010) work that clients in a supportive context have a stronger bond with staff member(s) that drive patterns of treatment. I suspect the supportive context network type was revealed because over two thirds of clients in this context are receiving treatment in CMHCs, which are known to embrace supportive treatment ideologies compared to SPH (Scheid 2004). Supportive contexts have the smallest average network size, suggesting clients are constrained to one or a few staff members. Clients may also perceive the elevated levels of supplied support and tend to drift toward these staff members that make up supportive contexts over time. Testing the causal order of network dynamics, however, requires longitudinal data and is beyond the scope of this study. Clients in a supportive context report the highest average frequency of contact, but there is no measure in this dataset as to the length of contact. Interestingly, my findings show that frequency of contact may not be an important factor in deriving clients' micro-cultural contexts, inconsistent with earlier typological research (Fiori et al. 2006; Wenger 1997; Wellman and Potter 1999). Whereas other characteristics do significantly vary between network types, how often clients talk with staff members does not significantly vary and is not a defining element of client-staff interaction.

Clients is a diverse context have similar implications on their working alliance to a supportive context. Diverse contexts are characteristic of being less functionally specific, having lower levels of support, lowers average multiplexity, and less frequent contact compared to the supportive context. Diverse contexts are also associated with a weaker working alliance. My results find the drastic difference of sexual support of diverse contexts compared to supportive contexts may explain the weaker predicted working alliance. The difference in sexual support levels is most likely due to majority of clients receiving treatment at SPHs, where discussion of sex and sex-related topics are much less likely. This is an example of how the larger clinical culture directs treatment ideologies and funnels down into client's micro-cultural contexts. Disentangling which, overall lower support or drastically lower sexual support, as having the greatest effect using the clustering analysis is not possible. The inability of my analysis to detect the nuance in the overall levels of supplied support *or* the specific levels of sexual support *or* the combination of all network features together, is a limitation of the typological approach (Li and Zhang 2015).

Clients in a sparse context, on average, perceive only one kind of support from each staff member and low functional specificity. My present analysis finds that staff members are less reliable than those in a supportive context and clients perceive staff to have a marginal presence in the treatment process. Further, clients in a sparse context have the least trusting relationship of any network type and may indicate that overall low levels of support and marginal general staff support is the worst for their working alliance.

Lastly, I found the two treatment oriented network types, clinical context and treatment-focused context. Both contexts are characteristic of higher levels of treatment related support with similar levels of average frequency of contact. In clinical context and treatment context, staff members are perceived to only fulfill the role as a treatment provider to clients. It is likely that I found two distinct treatment contexts because of the two name generators included in the clustering analysis, general staff support and treatment support, that are specific to staff members. Clients in a treatment-focused context are the most functionally specialized of any network context because they perceive staff members supplying only one kind of support, that is treatment.

Clinical context and treatment-focused context are both characteristic of contemporary ties as described by Pescosolido and Rubin (2000). Clients are social ‘outsiders’ to their affiliation with the treatment system because of their lack of internal integration. Clients relationships with staff members are contingent between the lay and professional for the purposes of treatment. Within clients’ social nets both contexts are *strung* together by a couple of threads and leaving clients at a high potential to not adhere to treatment programs, resulting in worse therapeutic outcomes. An additional note, clinical contexts are the least differentiated network type, sharing similar levels with a sparse context and diverse context. Thus, it seems the combinations of supplied support in addition to the number of staff members supplying a certain kind of support is relevant to client's working alliance.

Further analysis finds, that when clinical contexts are the reference group in the regression analysis (not shown, available upon request), clients in a treatment-focused context predict a decrease in their working alliance. Treatment-focused contexts are the most functionally specific network types and clients perceive a high percentage of staff members supplying only treatment support. Clients in a clinical context or treatment-focused context perceive their staff members fulfilling the treatment role but both are associated with a weaker bond between client and staff. With respect of less functionally specific contexts, clients perceived staff members supplying support beyond treatment and are associated with stronger therapeutic bond. Thus, predicting working alliance as an outcome is a measure for how network contexts shape client-staff interactions. My finding is consistent with earlier research (Ackerman and Hilsenroth 2001a) that staff members who are critical and distant toward clients either have trouble establishing or maintaining a working alliance. The characteristics of staff members beyond their role to treat is crucial for the perceived bond between client and staff. Clients in the treatment-focused context also have the lowest level of functioning (GAF score), which lead to poorer outlooks on treatment and thus a weaker working alliance.

Again, in order to understand how these micro-cultural contexts operate over time requires longitudinal data to examine network dynamics, I can only speculate as to the consequences of the structural and functional aspects of the network onto the client. I only investigate formal personal networks, whereas clients' external ties in the community may be larger suppliers of social support. Increasingly, studies demonstrate clients' reliance on external ties during the post-deinstitutionalization era (McConnel and Perry 2016; Perry and Pescosolido

2010, 2015; Schafer 2013), which may explain sparse context, clinical context, and treatment-focused context. If clients are receiving satisfactory levels of "important matters" support, health support, and sexual support in the community they may only seek treatment support from staff members. Future research into client's external ties of the IMHSHRS are needed to fully understand the perceived availability of support among clients.

5.2 Future Research and Implications

The finding from this study are set to contribute to the growing body of literature on social networks, mental health treatment, and meaning. Explicit exploration into the structural and functional features of personal networks reveal theoretically meaningful micro-cultural contexts of clients in treatment and their association with client level characteristics about their alters. According to Mohr and White (2008), meaning and identity are derived from the relations of actors' attributes to other actors' attributes in a network. Where in at the subjective level, client's motivations of "how they view the other" (Fuhse and Mützel 2011:1078) and client's expectations of staff members to improve their situation is how the relationship is understood. Thus, the meaning of staff members to the client can be inferred from their micro-cultural contexts and working alliance. For example, my empirical findings indicate clients in a supportive context are associated with a stronger alliance compared to other network types and in this context, clients report high levels of support. The meaning of staff members, here, is that they are helpful confidants in the treatment process, more specifically staff members are perceived to be willing to improve the client's situation by addressing other aspects of the client's wellbeing. The results of the client-staff relationship are constructed from interactions and negotiations that are captured in the name generators, specifically asking about discussions with staff members in the past three months. Here, the name generators are a proxy measure for the dynamic process of communication and the working alliance is the result of those interactions, creating meaning. My findings indicate that the combinations of specific interactions between client and staff and how frequently they occur are related to the client's perception of treatment.

On the other hand, clients in a treatment-focused context are associated with a much weaker alliance and therefore the meaning of staff members are strictly of treatment or even possible hinders in treatment. Client-staff discussions are limited to only treatment related topics and results in the subjective meaning of a less trusting alliance with the staff member. The staff member's attitude toward treatment are facilitated by organizational factors that direct treatment outcomes (Dobransky 2014; Scheid 2004). Future analysis will need to include treatment orientation variables to test for associations. What my finding do demonstrate is that the meaning of professional and lay can at least be partially explained by personal networks types.

A strength of the IMHSHRS data are the five name generators that provide a more nuanced insight into what is being discussed between the client and staff. Pulling from Bellotti's (2008) mixed method study of friendship, she was able to determine that the ego's description of friendship does not always align with the structural features of the ego's network. The meaning of staff to the client, then, often extends beyond that of the professional into someone they consider a close confidant (e.g. "important matters") or someone they can discuss sex with. Perry and Pescsolido (2010) demonstrate that alters whom the client discusses health do not necessarily appear in the "important matters" name generator. Likewise, sex may be a matter of importance, but since a separate name generator elicited ties, alters functions are further differentiated. A large part of understanding meaning in networks is recognizing that relations are based on communication and client's motivation. While my analysis cannot examine *how* the meaning was constructed over time, the implications of these interactions onto the client's perception of their therapeutic bond is tested.

My study presents evidence that the nuances of meaning can be partially parsed out with quantitative analysis when numerous name generators and name interpreters are available. Noting, however, that the cognitive burden of this on the respondent often makes this impractical or too costly for wide spread implementation. Further methodological development into the incorporation of cultural measures into personal network survey instruments is necessary to continue the investigation of meaning. Overall my study contributes to a growing body of literature into culture and networks with the use of quantitative techniques. While this does not yield the richness of a qualitative study, it does empirically demonstrate that subjective and inter-subjective meaning is associated with the network as a whole.

5.3 Limitations

My study has several important limitations. The analysis is limited to client's formal internal ties and is thus of a single 'plane' of support. The revealed network types are still multidimensional but are only composed of one type of alter, the staff member. It is then difficult to compare the clustering results with much of the existing literatures on community ties of personal network types. The results from the analysis do reveal insights into network typologies among clients with SMI and possible consequences in treatment. If clients perceived greater support that leads to greater trust of their staff members then they are more likely to adhere to treatment and have improved health outcomes.

Next, the cross-sectional data used does not allow me to examine the dynamics of network types. Longitudinal panel analysis would show how network types would change over time and can be compared with client and staff members characteristics. Further, staff member characteristics are not included in this analysis and would provide insights in the differences of clients' working alliance (Ackerman and Hilsenroth 2001a, 2001b). Including other variables of how long clients have been in their treatment facility and how long clients' have known each staff member would also provide additional information into where clients are situated in their illness career.

Third, the selection of variables used in the clustering analysis was guided by theory and the NEM framework. Instead, using a similar strategy like Wellman and Potter (1999) to determine key variables for constructing client network types would inform what elements are crucial in the client-staff relationship. Using one cultural measure narrows the analysis to one aspect of culture between the ego and alter(s). Including other scales in the analysis would allow a more comprehensive understanding of the cultural content in networks (Perry et al. 2018), by comparing other cultural measures through multi-mode network deigns. This is where qualitative studies would provide great insights into what is being discussed between clients and staff members, ripe for the relational sociology approach.

Finally, considering the order of which the name generators appeared in the survey instrument there is an increased probability of clients naming staff members in the "important matters", sexual, or health name-generators. All three appear before general staff and treatment support name generators, capturing staff members. It is possible, then, that less staff members would appear in the first three name generators ("important matters", health, and sex) if clients were asked the staff specific name generators beforehand. This would have led to different revealed network types and the implications for client's working alliance. Considering these limitations, future research into the network typologies of treatment systems for clients with SMI to better understand mental health treatment and larger patterns of social structures. The examination of meaning in networks requires serious development by network analysists and cultural theorists to help bring methodological advancements to the study of meaning in social networks (DiMaggio 2011; Emirbayer and Goodwin 1994; Fuhse and Mützel 2011).

6 CONCLUSIONS

I echo the calls made by network analysts and cultural theorists to incorporate the dimension of meaning into network analysis (DiMaggio 2011; Emirbayer and Goodwin 1994; Perry et al. 2018). Together, my findings advance our understandings of clients in treatment and personal networks by demonstrating that meaning is associated with client's working alliance. These results into the association of structural and functional features of client's networks informs treatment programs in recognizing that the perceived support supplied by staff members has significant effects on the client-staff relationship. The kinds and levels of support staff members supply is often beyond their direct role to treat, which can increase trust and ultimately improve client's treatment outcomes. In the midst of the post-deinstitutionalization era, increased burden is placed on community ties that are unstable over time (McConnel and Perry 2016). The results, here, highlight an opportunity for mental health programs to build-up stable support functions for clients, especially in times of crisis. Additionally, past network research shows the structure and function of networks have significant influence on individuals, further investigation into meaning may reveal other mechanisms of influence. My research points to the examination of culture and networks as a way to holistically understand influence in personal networks. Contributing to personal network and relational sociology research in that quantitative techniques can provide fruitful insights into subjective meaning of actors within networks. The need for continued mixed-method studies to understand the nuance cultural aspects of a network would allow a fully relational sociology approach of mapping words and phrases. In sum, this research reaffirms and continues the call for future empirical analysis into meaning in personal networks.

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