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Dynamic Social Networks

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This chapter will provide an introduction to dynamic social networks. The first part of the chapter will present an overview of the theory and methodology of dynamic social networks, with particular attention to its usage in community-based research on friendship and mentoring. This will then be followed by a case study illustrating the application of this approach to the study of substance abuse recovery residences.

INTRODUCTION TO DYNAMIC SOCIAL NETWORKS

Personal Networks

Network studies in community-based research have typically been based on personal network data (also called "ego networks"). Personal networks are assessed by asking an individual ("ego") to identify his or her relationships ("alters"), which can be close friends, family members, and work associates. This identification allows the investigator to infer that the same person is being named in successive assessment occasions. Ego is also asked to rate each alter on various characteristics such as behaviors (e.g., substance use, current or past criminality). From such data, it is possible to calculate, for instance, the percentage of ego's friends who are using various substances and to track changes in this composition over time.

Personal network methodology offers greater detail in measuring social context compared to simple summary ratings. As an example, *turnover* describes the percentage of change in network composition for individuals from one time point to another. Although it is possible to assess this social context variable by a general question, such as "How much change has there been in your friendships since the last survey?," these measures are open to individual interpretation and may be unreliable. Alternatively, turnover can be *calculated* from personal network data. As an example, Stone, Jason, Stevens, and Light (2014) studied a sample of individuals in recovery from substance abuse and found less turnover in networks when alters were relatives of the person in recovery, abstinent from drugs, and had frequent contact with the person in recovery.

The personal network has a long history in our field (Groh, Jason, & Keys, 2008). Kornbluh and Watling Neal (see Chapter 21) identify network measures that characterize settings (e.g., density and reciprocity), actors (e.g., centrality and power), and actor dyads (e.g., structural equivalence and geodesic distance). This approach was used by Wrzus, Hänel, Wagner, and Neyer (2013), who found that the *sizes* of individuals' personal and employment networks varied with age and life events. Global networks decreased on average by about one person per decade after young adulthood, while the size of the family network remained stable. Divorce was associated with a decrease in the size of the family network, and death of a relative was associated with a decrease in global network size but an increase in the size of the closer personal network.

In the realm of substance use, Vaillant (1983) noted that environmental factors may be key contributors to maintaining abstinence after treatment. These factors include the amount and type of support one receives for abstinence. Individuals who participate in aftercare services sustain abstinence for a longer period of time (Laudet, Becker, & White, 2009). One study found that each additional month spent in aftercare led to a 20% increase in the odds of continued abstinence (Schaefer, Cronkite, & Hu, 2011). Supporting this line of research, Buchanan and Latkin (2008) examined the personal networks of heroin and cocaine users, finding that those who quit had a significant change in the composition of their social network from pre- to postcessation.

Whole Networks

With personal network research we are able to understand how one person perceives the relationships that comprise his or her network, but this provides only half of the story, as dyadic relationships are inherently concerned with both members. As an example, a child might rate how much support he or she feels from each friend for refraining from smoking. This is an important piece of information, but it does not tell us whether his or her friends actually support this youth's effort to not smoke, nor how they perceive the relationship. In contrast, a whole network approach would have every member of a network rate each other on relational issues, such as support for not smoking. Whole network approaches provide a relational map of an entire social ecosystem, capturing each individual's perspective, and it becomes possible to model how these potentially differing perspectives interact as time goes on. Thus, dynamic models of whole social networks focus on the mutual interdependence between relationships and behavior change over time, providing a framework for conceptualizing and empirically describing two-way transactional dynamics.

The Stochastic Actor-Oriented Model (Snijders, van de Bunt, & Steglich, 2010) provides a statistical framework for fully transactional models. In this modeling framework, social networks are conceptualized as a set of individuals whose relationships evolve over time according to an underlying probability structure. This process can depend on a linear combination of predictors, which are interpretable as hypothesized mechanisms that jointly predict network evolution. Model effects include both fixed (e.g., gender and ethnicity) and time-varying (e.g., attitudes and behaviors) measured characteristics of individuals, which are familiar from ordinary regression modeling. However, effects associated with dyads (pairs of individuals) are also possible, as well as effects associated with an individual's structural embedding (number of linkages with various alters, possibly with particular characteristics, or who lie along a similarity continuum on some behavior, for example). The latter effects exemplify a major contribution of the network perspective to the study of social relationships, namely, that relationship dynamics depend not only on individual characteristics, needs, and preferences but also on the state of the network and individuals' positions within it. There are many potentially important structural effects that can be examined with the Stochastic Actor-Oriented Model, depending on the substantive network being studied. For human relationships, two such effects are reciprocity (i.e., the tendency for relationships to become reciprocated or be dropped) and transitivity (i.e., the tendency for all members of triads to share the same relationship).

Although a transactional interchange between the individual and his or her social environment is an essential component of community psychology (Jason & Glenwick, 2012), methods for studying these systems are still quite limited. As an example, even advanced statistical techniques such as multilevel modeling are primarily useful for studying the effect of context on behavior and, despite some generalizations (e.g., Kenny, Mannetti, Pierro, Livi, & Kashy, 2002), does not extend to the effects of behavior on context naturally or broadly (e.g., Todd, Allen, & Javdani, 2012). A whole network approach can provide a methodological framework for thinking about and describing two-way transactional dynamics. Work in this area is part of what is considered systems research, in that interest centers on how microlevel mechanisms (e.g., how we both influence and are influenced by others) aggregate to the macrosystem level and then feed back to the microlevel in an ongoing causal loop.

Part of the reason for the popularity of personal network methodology in community psychology research is undoubtedly its tractability. In contrast, whole network data require the researcher to identify some relatively closed social ecology and assess all or nearly all of its members; these assessments must be carried on repeatedly over a substantively meaningful period of time in order to observe and model change. For many community-relevant units, especially geographical areas such as neighborhoods, this is obviously difficult. If no natural, fully assessable group of interest is available for a given network study, the personal network approach is attractive. It permits a more granular assessment of individuals' social contexts than do simple individually based summary ratings or perceptions, while still providing a tractable measurement strategy based on measurements from independent individuals.

Nevertheless, where whole network assessments are possible, such data confer considerable advantages. Examples of such situations include school-based child or adolescent friendships. In these settings, whole network models can separate effects of exposure to friends' behavior from the tendency to select behaviorally similar others as friends. As an example, using school-based longitudinal network data, Weerman (2011) found that exposure to delinquent friends had a significant (although small) effect on youths' own delinquency, but, contrary to common assumption, there was no tendency for friendship selection based on similarity of delinquent behavior. Another school-based network study by Mercken, Steglich, Sinclair, Holliday, and Moore (2012) found that similarity in smoking behavior among adolescent friends emerged from the linked mechanisms of selecting similar friends and the subsequent influence of those friends on behavior. Complete network methodologies are particularly well suited to measuring and explaining the dynamic interplay among friendship and other relationships, and attitude and behavior change, simultaneously identifying the active *social* mechanisms underlying these changes.

Friendship and Mentoring

Friendship and mentoring has become a major area of research in the field of community psychology (Rhodes & DuBois, 2008), and social network methodology represents a novel possibility for exploring these constructs. The study of friendship has a long tradition in group dynamics and social psychology research and theory. Friendship has, of course, also been a primary focus of network science since its inception (Moreno, 1934). In many of our social and community interventions, trust is a critical precursor of close relationships (Bonaventura et al., 2006; Horst & Coffé, 2012), and that trust is recognized as an essential ingredient of the development of friendships in a wide variety of settings (e.g., du Plessis & Corney, 2011; Way, Gingold, Rotenberg, & Kuriakose, 2005). Trust tends to develop in groups in part as a function of interindividual exposure (Patulny, 2011), especially when the individuals in the group are dependent on each other for desired outcomes (Schachter, 1951).

A body of classic literature explains how and why groups of different sorts experience conflict and how these groups can be brought together to develop friendships. For example, Sherif (1966) described two sets of boys at a summer camp who competed with one another in various events. Stereotypes developed, resulting in escalating hatred and aggressive behaviors. Sherif next attempted to reverse the rivalry by creating challenges that required cooperation between the two groups. In one instance, if either group wanted to see a movie on a particular evening, they had to pool their funds with the other group. These exercises were effective in reducing the negative feelings and aggression between the groups. Sherif interpreted these results in terms of superordinate goals, that is, goals that groups could share, even in the presence of ongoing differences. These superordinate goals bring individuals together and can counter other differences. Such research suggests that those community settings and groups that promote interdependence will foster friendship and trust, and these settings should mutually reinforce each other in a positive feedback loop. The key is to be able to have the methodological sophistication to capture these reciprocal feedback loops that occurred in Sherif's work and in much of the friendship and trust literature. This, we suggest, is exactly what the Stochastic Actor-Oriented Modeling framework offers: a method that can estimate transactional models from longitudinal, survey-based social network data.

In network studies of formal organizations, asymmetrical relationships are common due to recognized differences in expertise, even when rank is not formally designated within the group in question (e.g., a managerial hierarchy) (Snijders & Bosker, 2012). The mentor-friend distinction is well grounded in network and organizational theory and motivates a focus on conditions that promote the formation of each type of relationship. Because expertise asymmetry is typical of mentor relationships, it seems likely that these relationships will also tend toward asymmetry.

Mentorship relationships are conceptualized from the perspective of the social support literature. Close friendships are in most cases a source of mutual support. By contrast, mentors typically hold higher status positions, supplying mentoring and support in exchange for respect and gratitude, for example. According to social exchange theory (e.g., Blau, 1964), the asymmetric exchange of dissimilar goods or services is characteristic of hierarchical social relationships.

Such relationships are assumed to coevolve over time, affecting and affected by attitudes and behaviors and personal networks outside the group or setting. In recent years, whole network studies have opened a new level of insight into the social dynamics within a variety of areas, including substance use, especially among youth (e.g., Veenstra, Dijkstra, Steglich, & Van Zalk, 2013) but also in adult populations (Cruz, Emery, & Turkheimer, 2012). This approach has led to major advances in, for example, our understanding of the role of peer affiliations in substance use among adolescents (Brechwald & Prinstein, 2011; Dishion, 2013), for whom schools provide natural social laboratories because of their organization of youth into same-age cohorts, which often include nearly all such youth in a given community. Moreover, although studies of multiple types of network relationships are not new (e.g., White, Boorman, & Breiger, 1976), dynamic models of such "multiplex" networks have only just begun to appear (Snijders, Lomi, & Torló, 2013).

In the next section, we present a case study as an example of a multiplex dynamic social network study, using data from a small sample of recovery homes to examine some of the concepts discussed earlier. Because each recovery house is a complete network of relationships, it is possible to think of each as an independent set of relationships that coevolve over time with changing resident characteristics such as recovery-related attitudes and behaviors. Each house is treated as an independent network, but the Stochastic Actor-Oriented Model is used to create a model that is assumed to be driven by the same mechanisms across houses.

CASE STUDY

Drug abuse and addiction are among the costliest of health problems, totaling approximately $428 billion annually (National Drug Intelligence Center, 2011). In 2012, an estimated 23.9 million Americans aged 12 years or older were current illicit drug users (US Department of Health and Human Services, 2012), which represents 9.2% of the population aged 12 years or older. Unfortunately, many people who finish substance use treatment relapse within a few months (Vaillant, 2003), which might be due to the lack of longer term community-based housing and employment support (Jason, Olson, & Foli, 2008).

A number of self-help organizations, including Alcoholics Anonymous (AA), provide support to individuals following treatment, but such programs do not provide needed safe and affordable housing or access to employment. For these needs, a variety of professionally run and resident-run residential programs are available in the United States (Polcin, Korcha, Bond, Galloway, & Lapp, 2010). Although such recovery programs are important sources of housing and employment support, they do not work for everyone (Moos & Moos, 2006). For instance, early dropout from recovery homes often occurs due to a new resident's failure to become integrated into the house social ecology (Moos, 1994). The dynamics of social integration in recovery houses may be studied by conceptualizing them as social networks that evolve based on both structural tendencies and network members' characteristics.

It is plausible that a recovery house stay benefits residents in the same way as AA involvement, in being a source for alternative friendships, modeling, advice, and support. Thus, predictors of strong within-house relationships would be important to investigate. Relevant relationships would be those that promote discussion of recovery-threatening topics, for example, such negative feelings as stress, anxiety, and loneliness. Such people, which could be called confidants, are also important as a source of interactive problem solving that is less likely in 12-step meetings.

Some recovery houses, such as Oxford Houses (OHs), do provide comprehensive social environments for residents. OHs are the largest single network of recovery houses in the United States, with more than 10,000 individuals in some 1,700 houses at any given time. OHs are rented, single-family homes with a gender-segregated capacity for 6 to 12 individuals. Residents must follow three simple rules, namely, pay rent and contribute to the maintenance of the home, abstain from using alcohol and other drugs, and avoid disruptive behavior. The OH model of substance abuse aftercare is a standardized program with low start-up and maintenance costs (see Substance Abuse and Mental Health Services Administration's National Registry of Evidence-Based Programs and Practices, 2011).

The first author and his team have been studying recovery houses for over two decades. In our initial work, personal network data produced some intriguing results and led eventually to collecting data with whole networks. In one early study, we examined abstinence-specific social support and abstention from substance use in a national sample of OH residents. We found that only 18.5% of the participants reported any substance use over 1 year (Jason, Davis, Ferrari, & Anderson, 2007). Additionally, over the course of the study, the proportion of abstainers in individuals' personal social networks increased. Those with other OH residents as part of their social network were more likely to stay in OH at least 6 months and were less likely to relapse (Jason, Stevens, Ferrari, Thompson, & Legler, 2012). These findings provided us a hint of the importance of friendships within OHs as a mediator of positive outcomes.

In another study (Jason, Olson, Ferrari, & LoSasso, 2006), we successfully recruited 150 individuals who completed treatment at alcohol and drug abuse facilities in the Chicago metropolitan area. Half of the participants were randomly assigned to live in an OH, while the other half received community-based aftercare services (referred to here as Usual Care). At the 2-year follow-up assessment, the relapse rate for those individuals with 6 or more months of OH residency was 15.6%, while the rate was 45.7% for those individuals who stayed less than 6 months. For the UC group, the relapse rate was 64.8% (Jason, Olson, et al., 2007). In other words, staying in an OH for at least 6 months was critical for extremely high abstinence rates. For those residents who stayed 6 months or longer, the overall size of the personal network and the number of recovering alcoholics in that network increased, while the number of light drinkers decreased (Mueller & Jason, 2014). Significant changes occurred over those first 6 months with respect to likelihood of employment, change in median abstinence self-efficacy, and percentage of sober members in the individual's list of people considered of importance in their lives (Jason, et al., 2012). For example, the median abstinence self-efficacy for the OH sample increased significantly in the initial 6-month measurement period, the unemployment rate dropped by over 52 percentage points, and 100% of the most important people in their social network became sober.

Longitudinal network modeling methods were then utilized to help provide insight into house-level social dynamics that might affect length of stay. Although the time frame for this small study was too short to reliably estimate effects of dynamics on actual attrition, based upon prior studies we hypothesized that predictors of the tendency to form supportive relationships would provide useful input regarding this question. Our model postulated a set of relationships among recovery-related behaviors and attitudes, interpersonal trust, and both mentoring and friendship relationships. Risk-regulation theory (Murray, Gomillion, Holmes, Harris, & Lamarche, 2013) suggests that a resident will avoid other residents with low behavioral commitment to recovery because they threaten the residents' own recovery. In this model, trust develops from evidence of common recovery goals, as exemplified by similar recovery-related behaviors and attitudes, and then mediates the formation of close relationships (Rempel, Holmes, & Zanna, 1985).

We assume that a particular group to be studied can be meaningfully represented in terms of (a) a set of relationships of a particular type among group members—a "social network" N_r—with the added possibility that several such networks may be defined on a group, and some may be ordered, representing gradations of some abstract relationship; (b) a set of both fixed and time-variable characteristics that can be measured for each group member; and (c) a set of predictive interrelationships of the form $P(Y_t = y) = f(X_{t-\varepsilon})$, where X is a predictor, and $P(Y_t = y)$ is the probability that outcome Y has value y after the actor makes a decision (where y can be –1, 0, or +1, representing a change of at most 1 unit from the value of Y just prior to time t, that is, time $t - \varepsilon$). This conceptual formulation is consistent with the objective of modeling social integration processes (that is, changes in relationships) in recovery houses. We hypothesize that relationship closeness and trust will be positively and causally linked; if we let X be trust and Y be relationship closeness, then

$$P(Y_t = y) = f(X_{t-\varepsilon})$$

$$P(X_t = x) = g(Y_{t-\delta})$$

Thus, earlier trust ($X_{t-\varepsilon}$) predicts the probability of a change in later relationship closeness (Y_t), and vice-versa, net of other predictors that are included primarily to make causal inferences more plausible

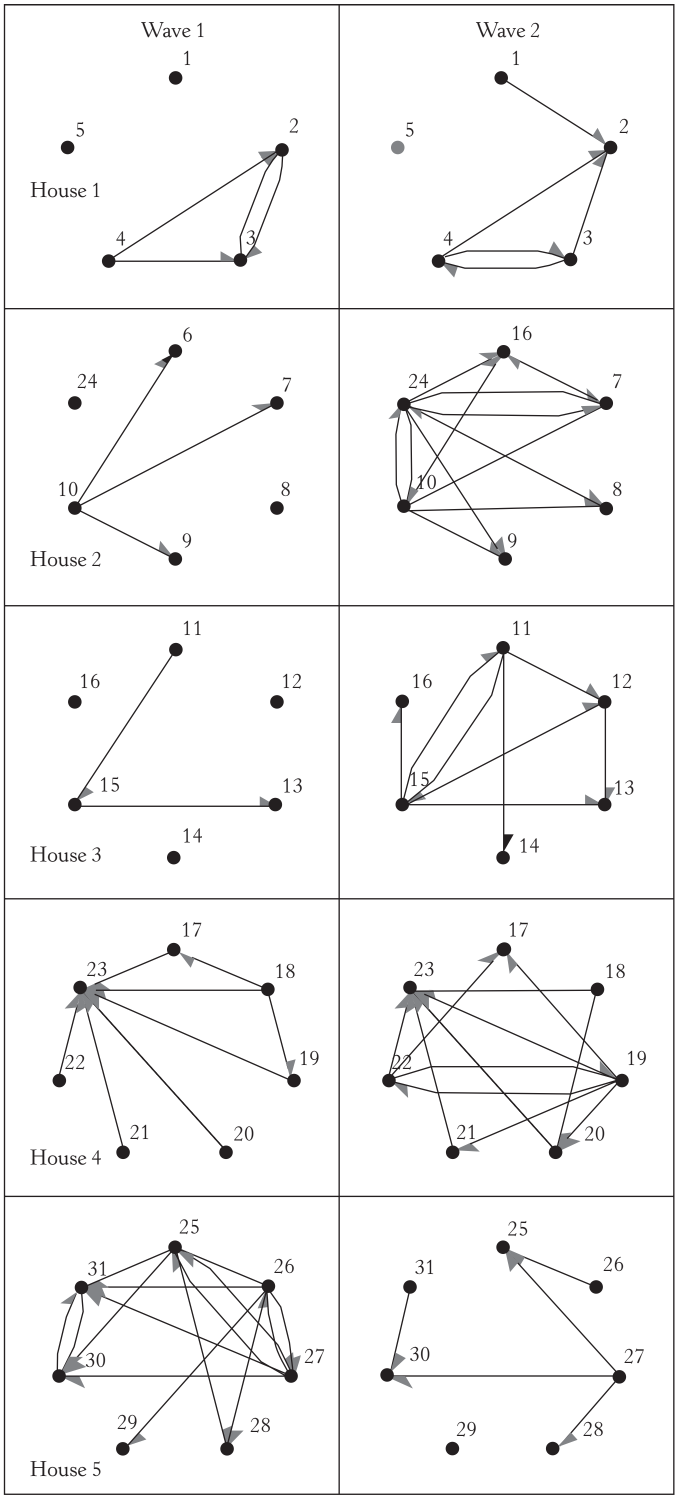

FIGURE 22.1 "Confidant" relationships for each Oxford House over time (Wave 1 and Wave 2).

Source: "Dynamic Social Networks in Recovery Homes" by L. A. Jason, J. M. Light, E. B. Stevens, & K. Beers, 2013, *American Journal of Community Psychology, 53*(3-4), p. 324–334, Figure 2. © Society for Community Research and Action 2013. Published with kind permission from Springer Science+Business Media.

(Fisher, 1934). It is important to bear this in mind as we present results that "predictors" do not predict the value of an outcome variable in this type of model; rather, they predict *change in* an outcome variable. This is a somewhat different perspective than the reader may be familiar with from ordinary regression and other covariance structure models.

We collected baseline and 3-month follow-up house-wide whole network data from five OH recovery houses with 31 participants (Jason, Light, Stevens, & Beers, 2014). Results from a Stochastic Actor-Oriented Model examining interrelationships among different levels of trust and formation of confidant relationships showed that (a) residents who had lived in the house for longer periods of time were more likely to be highly trusted, (b) high trust predicted formation of confidant relationships, and (c) confidant relationships were not regularly reciprocated. Confidant relationships showed no pattern of reciprocation, suggesting that they are not like friendships, which normally do evidence such a pattern. Figure 22.1 shows how confidant relationships were not necessarily likely to be reciprocated (Jason et al., 2014, p. 328). Of the 24 baseline dyadic confidant links among participants, only 12.5% were symmetrical; and at follow-up, only 10% were symmetrical. This suggests role specialization, and in confidant relationships, there is a confider and a listener. Friendships, by contrast, tended to become symmetrical, as a much higher percentage of trust relationships were reciprocated; at baseline, 59% of dyads trusted each other symmetrically, and at follow-up, 70% trusted each other symmetrically. In addition, trust relationships become increasingly likely the more one has them. These are called "outdegree" effects, and they suggest a threshold effect for trust, in the sense that once a person is trusted "somewhat," it is likely that he or she will eventually be trusted even more and that trusting others highly becomes self-reinforcing (Light, Jason, Stevens, & Stone, unpublished data).

That (a) formation of "high-trust" relationships is positively related to time in residence and (b) high trust is necessary to the formation of confidant relationships begins to sketch the outlines of a dynamic pathway to a successful residence experience. In other words, successfully finding a confidant or mentor may be a key pathway for continued sobriety. Although this model was necessarily simple, convergence for the model was excellent (Jason et al., 2014). All parameter *t* ratios were <0.05 (below 0.10 is considered good convergence; Snijders et al., 2010). Also, we obtained reasonable estimates of all parameter standard errors. Our study suggests that the innovative Stochastic Actor-Oriented Modeling approach is a feasible and promising empirical framework for studying evolving house social ecologies.

In the same data set, we also found that individuals who reported higher levels of general social support also reported higher levels of self-efficacy (Stevens, Jason, Ram, & Light, 2014). In addition, a larger social network predicted lower perceived stress. These findings merit further exploration regarding how and if social network size may be related to social support and the characteristics of social network size that relate specifically to promoting abstinence. They provide a strong basis for continuing to examine physical social network properties and their possible influence on an individual's psychological state.

CONCLUSION

This chapter has focused on dynamic social network models, a paradigm that is distinguished from other approaches by its emphasis on the mutual interdependence between relationships and behavior change over time. As such, it provides a framework for conceptualizing and empirically describing two-way transactional dynamics. The chapter reviewed studies using complete network data (i.e., where all possible dyadic relationships among individuals or other entities, such as organizations, are accessible), providing a structural map of an entire social ecosystem. We also provided an example showing how the dimensions of trust, friendship, and mentoring change over time in the relationships among persons living in substance abuse recovery residences.

There are several other frameworks available for modeling the coevolution of trust and relationship closeness. For instance, the Actor-Partner Interaction Model (Kenny et al., 2002) offers a way to estimate effects of personal characteristics apart from relationship partner effects on behavior change. On the other hand, it takes relationships as fixed, and hence cannot model behavioral and relational (dyadic) interdependence. Gottman, Swanson, and Murray's (1999) Linked Difference Equation model is an example of the differential (in continuous time) or difference (in discrete time) modeling approach originally applied to physical systems (e.g., Newton's laws of motion can be written in differential equation form). It has been useful for other scientific applications, for instance, mathematical biology (Murray, 2003) and child development (van Geert & Steenbeek, 2005). Structural equation modeling methods have been developed to estimate the parameters of such systems (Hu, Boker, Neale, & Klump, 2014; Voelkle, Oud, Davidov, & Schmidt, 2012).

The Stochastic Actor-Oriented Model is a specific application of differential equation modeling. It shares with such models an inherent "generative" nature, meaning that its temporal evolution can be simulated in a natural way (Snijders & Steglich, 2015). Unlike the deterministic models mentioned earlier, the underlying dynamics can be written as a set of stochastic differential equations, which is often substantively preferable for modeling complex, multidetermined systems. Conceptually, such systems are unlikely to evolve exactly the same way, given a particular set of initial conditions. The solution to a stochastic differential equation will be a stochastic process, which under the assumptions of a Stochastic Actor framework is a continuous-time Markov process. Abstractly, such models provide the type of continuous-time "transactional" representations required to realistically model relationship-behavior dynamics.

Pragmatically, moreover, such modeling has been well developed, extended, and thoroughly documented over the last several decades. Models may be estimated with publically available free software that is actively maintained and upgraded: the RSiena package for the statistical software environment R. Hundreds of relationship and behavioral effects can be modeled, and programming-oriented users can add their own. A suite of estimation methods based on tried and true statistical theory include Bayesian, maximum likelihood, and, for larger samples, a faster score function-based approach. Multilevel methods are built in, permitting variously pooled models across networks and other entities. Data requirements are clearly defined and based on familiar survey methods (although other data collection methods could also be used). This methodology is still developing, and some important aspects of it have yet to be evaluated, for example, the Markov assumption, which amounts to assuming that each "decision" made by an actor is unaffected by the history of the system prior to the time of the decision. Such weaknesses must be weighed against those of other available methods.

In this chapter we have presented a social network as both a theoretical/conceptual and an empirical entity. Conceptually, we think of it as a map of particular types of dyadic relationships in a bounded social group. Empirically, a network can be straightforwardly measured, for example by direct observation of interactions or, as in our example, by asking group members to nominate others as relationship partners. The network paradigm provides a particularly convenient framework for dynamic analysis of a set of developing social relationships.

This convenient grouping of a target population is not typical for adults; even studies of networks in organizations by no means include all relevant social contexts for organizational members, such as family and leisure companions. A limiting factor in whole network research is identifying a group where all the members of the network know each other, and another is having access to all these individuals for ratings. In contrast, personal network studies of substance use recovery have established the relevance of participant-reported associates as mediators of ongoing sobriety (Kaskutas, Bond, & Humphreys, 2002; Polcin et al., 2010). However, as mentioned earlier, personal networks are inherently limited by their reliance on the perceived relationships of a person and other network members, rather than on all of the relationships in a system.

The use of dynamic social networks provides a higher-magnification lens for understanding contextual influences on behavior and behavioral influences on context. For example, we can learn how an individual may influence the existing network, not just how an existing network may affect the individual's behavior. Questions that this approach will eventually help us understand may include the following: How do new individuals fit into this ecology—or fail to? What do they need to take away from it in order to succeed in settings? Are there more systematic ways individuals could prepare for entry into a setting? How do relationships within a setting, as well as within their own personal networks, interact? The answers to such questions lie in the study of the way setting cultures develop, are maintained, and are extended to new individuals, and how this process interacts with attempts to refashion personal networks to support a variety of personal goals. A novel adaptation of dynamic network modeling could help us answer questions such as these.

The work we have described in the case study was based on a complex system that involves those recovering from addiction and two social ecologies (their recovery house and personal network). Our perspective is naturally transtheoretical. At the level of the individual, Moos (2007) and Vaillant (2005) offer rationales for why integration into the house social system should be important to recovery house effectiveness, such as resultant bonding, monitoring, goal direction, modeling, positive reinforcement, rewarding alternatives to using, and advice and outlets for dealing with negative emotions and stress. Because relationships within the house (and/or in the personal network outside the house) are likely to be vehicles for these processes, integration can be viewed as relationship formation processes. Furthermore, as Valliant explicitly noted, many of these recovery-supportive processes are likely to be active in new, recovery-supportive friendship and mentoring relations. Dynamic social networks provide us with the ability to focus on processes whereby those relationships form in the house or support their formation in the personal network outside the house, and especially how friend and mentor relations affect recovery outcomes.

Our research has provided significant insight into house structure and dynamics as predictors of an individual's likelihood of maintaining a positive recovery trajectory. We have been able to identify contributions of external recovery behaviors (e.g., AA), external ego-centered networks (scope, composition, dynamics), and within-setting social networks. These mechanism-level effects are empirically verifiable and interesting in their own right, but the behavior of such a complex system as a whole is not immediately obvious. This sort of information can be obtained by simulation, however. Stochastic simulations will give rise to a distribution of outcomes of interest, such as the probability of developing a stable social support system within and outside the house, leaving the house prematurely, and relapsing. The models can also be studied to determine promising mechanisms that could be affected by changes in house operations, individual-level interventions, and so on, and possibly failure thresholds where the likelihood of poorer outcomes begins to accelerate. Thus, by identifying mechanisms through which social environments affect health outcomes and looking at system-level evolution, this approach could contribute to reducing health care costs by improving the effectiveness of the residential recovery home system in the United States and also restructuring and improving other community-based recovery settings. In addition, our work provides an initial framework for the study of network dynamics in recovery homes that may facilitate both the theoretical development and empirical investigation of the broader domain of recovery in community-based settings following treatment.

In summary, our social network design and resulting mathematical model provide a conceptually useful way to represent social system dynamics in relation to progress toward self-sustaining recovery. Substantively, our work using dynamic social network theory and methodology has addressed the longstanding question of how and why community-based settings support sobriety, perhaps moving this option more into the mainstream of substance abuse treatment protocols. This is but one example of the many social problems involving complex relationships between individuals and their social environments that could benefit from a dynamic social network approach.

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SECTION III

Mixed Methods Approaches