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Reducing Readmissions to Detoxification: An Interorganizational Network Perspective

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Abstract

Background—The high cost of detoxification (detox) services and health risks associated with continued substance abuse make readmission to detox an important indicator of poor performance for substance use disorder treatment systems. This study examined the extent to which the structure of local networks available to detox programs affects patients' odds of readmission to detox within 1 year.

Methods—Administrative data from 32 counties in California in 2008–2009 were used to map network ties between programs based on patient transfers. Social network analysis was employed to measure structural features of detox program networks. Contextual predictors included efficiency (proportion of ties within a network that are non-redundant) and out-degree (number of outgoing ties to other programs). A binary mixed model was used to predict the odds of readmission among detox patients in residential (non-hospital) facilities ($N=18,278$).

Results—After adjusting for patient-level covariates and continuity of service from detox to outpatient or residential treatment, network efficiency was associated with lower odds of readmission.

Conclusion—The impact of network structure on detox readmissions suggests that the interorganizational context in which detox programs operate may be important for improving continuity of service within substance use disorder treatment systems. Implications for future research are discussed.

Keywords

detoxification; coordination of care; network analysis; multilevel modeling

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Detox Network Paper- Author Disclosures

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No conflict declared

1. INTRODUCTION

One major service gap in the continuum of care for substance use disorders is the engagement of patients in treatment or rehabilitation after detoxification (detox). Multiple admissions to detox are common in the United States. One study found that 11.3% of patients who receive detox services reenter detox two or three times, indicating not only the chronic nature of addiction but also inadequate care and inefficient use of public resources (McLellan et al., 2005). In California, for example, only 23% of detox admissions result in transitions to substance use disorder (SUD) treatment (Urada et al., 2010). At the point of discharge from detox, patients are at high risk of relapse and therefore vulnerable to system failures. Detox alone increases patients' risk of mortality from overdose if they do not transition to SUD treatment after discharge (Urada et al., 2010; Wines et al., 2007). The need to improve coordination of care from detox to SUD treatment is critical.

Research on the problem of detox readmissions has identified a number of patient- and program-level factors associated with detox readmissions. Patient-level factors associated with detox readmissions include alcohol as the primary drug problem, drug use severity, residential instability, older age, unemployment, single marital status, Hispanic ethnicity, lack of follow-up rehabilitation care, and health coverage through fee-for-service Medicaid plans (Callaghan and Cunningham, 2002; Campbell et al., 2010; Carrier et al., 2011; Mark et al., 2006). Continuity of service between detox and SUD treatment is seen as an important means of reducing readmission to expensive forms of treatment such as detox care, increasing retention in less intensive forms of treatment such as outpatient care, increasing availability of detox for more individuals in need, and ensuring patients are served at the appropriate level of care (Mark et al., 2006; McLellan et al., 2005). Research suggests that program-level factors such as smaller program size, closer proximity between detox and SUD treatment facilities, and discharge planning are associated with continuity of service (Campbell et al., 2010; Carroll et al., 2009; McLellan et al., 2005). Implicit in the continuity of service framework, however, is the existence of interorganizational relationships among SUD treatment programs. Garnick et al. (2009) acknowledges this assumption by noting that the "rationale is that the residential facility has made the connection with the next level of care after discharge" (p. 271). These connections, however, cannot be taken for granted given the reputation of SUD treatment systems for being fragmented (McLellan et al., 2003; Saitz et al., 2008).

The current study expands upon prior research on patient- and program-level predictors of detox readmissions by examining the role of interorganizational networks. An interorganizational network perspective assumes that the ability of service organizations to achieve their goals for patient care depends in part on the relationships they have with other organizations. Interorganizational relationships and cooperative arrangements between health and human services providers are associated with improved access to care, enhanced service quality, and reduced costs (Alter and Hage, 1993; Provan and Milward, 1995; Rogers and Whetten, 1982).

Application of Network Theory to the Problem of Continuity of Service

Network analysis is a set of theories and methods for studying social interaction among three or more actors, which can be individuals, organizations, or other units of analysis. Network analysis focuses on the relationships between actors rather than the individual attributes of individual actors. This study was grounded in network theory, which explores how network structure affects the availability of resources and performance of organizations. Networks reflect social structures, which are created from various types of exchanges between organizations. Morrissey et al. (1985) called these exchanges “resource flows,” and the types of resources in the context of service delivery systems can include referrals, information, and services. Network analysis research has found that social ties are valuable to organizations for the development of financial capital (Uzzi, 1999), innovations (Ahuja, 2000; Burt, 2004; Liebeskind et al., 1996), and integration health and human services (Provan and Milward, 1995; Provan and Sebastian, 1998; Rosenheck et al., 2001).

One structural feature of networks that has been shown to provide individual actors with a competitive edge is known as a “structural hole.” Structural holes occur in networks when some actors within the network are not connected to each other. Structural hole theory suggests that if all actors within a network are connected to each other, information and resources become redundant because everyone has access to the same information and resources. Similar to the “theory of weak ties,” structural hole theory suggests that having non-redundant ties within an network is advantageous because they can help actors access information and resources outside their social circle (Ahuja, 2000; Burt, 2000; Granovetter, 1973).

Redundancy implies that detox programs and their ties to other detox and SUD treatment programs transfer patients among themselves. These redundant ties create closed organizational networks, which, in the current context, may result in a limited set of treatment options for patients. Structural holes, however, may create opportunities for detox and SUD treatment programs to transfer patients to other programs beyond their immediate network, thereby expanding their referral networks. For a detox program, having a broader range of referral options may facilitate continuity of service for patients if the services provided within the detox program's immediate network are not appropriate for patients' needs and preferences. This study hypothesized that patients served by detox programs with fewer redundant ties in their networks would have lower odds of readmission to detox.

2. METHODS

2.1. Sample

This study used administrative data from the California Outcomes Measurement System (CalOMS). CalOMS is a state data collection and reporting system for alcohol and other drug treatment services that reports to the federal Treatment Episode Data Set. CalOMS requires all publicly funded treatment providers to provide admissions and discharge data for all patients regardless of funding source. CalOMS includes information on alcohol and drug use, criminal justice involvement, employment and education, family and social support, and physical and psychological health. The collection form includes 10 items from

the Addiction Severity Index (McLellan et al., 1980) and the Drug Abuse Reporting Program (Simpson, 1984; Simpson and Sells, 1982). These scales have been shown to be reliable measures of substance abuse severity (Weisner et al., 2000), particularly among diverse populations (Longabaugh, 1991), allowing for assessment of patient characteristics from intake to discharge.

The administrative data included 150,955 patients who had a total of 440,496 admissions to treatment or detox services from July 1, 2008 to June 30, 2009. The sample of detox patients used for this analysis included all patients in the administrative record who were admitted to a residential detox program between July 1, 2008, and June 30, 2009 ($N = 18,278$). The patients were treated by 1,600 individual programs or service delivery units, i.e., single programs such as residential rehabilitation and outpatient counseling within service organizations. The data included a total of 57 residential detox programs. To observe readmissions to detox within 1 year of discharge from the initial detox admission, an additional year of data was included in the dataset (July 1, 2009 to June 30, 2010).

2.2. Network analysis

Data from all patients admitted to publicly funded substance use disorder treatment services between July 1, 2008, and June 30, 2010, in 32 California counties were used to identify ties between service units. The 32 counties were selected from a total of 56 counties because they reported admissions data for detox programs in their counties. In the sample, there were 13 large counties (more than 800,000 people), 10 medium counties (250,000–800,000 people), and nine small counties (90,000–250,000 people; County Alcohol and Drug Program Administrators' Association of California, 2006). The majority of detox admissions in the state were from Los Angeles, San Francisco, Alameda, and San Diego counties.

Network ties were based on patient transfers between all types of SUD treatment programs, e.g., free-standing residential detox programs, outpatient detox programs, residential programs, outpatient drug-free programs, and outpatient methadone programs. Transfers were defined as a new admission to any SUD service program within 14 days of discharge from a prior program (Garnick et al., 2002). Transfers, as defined in the current study, can flow in any direction and between all types of programs, e.g., detox to treatment, treatment to detox, detox to detox, and treatment to treatment. That is, programs gain ties when their patients transfer out to other programs and when patients transfer into their program. The networks were based on binary ties; that is, the number of transfers between programs was not considered in this analysis. The 14-day time frame has been used to define patient transfers for the purpose of performance measurement (Garnick et al., 2009). Prior research on transfers in CalOMS found that the mean number of days between services during a transfer was 6.8 and the median was 3 days; therefore, the window of 14 days sufficiently captures most patient transfers (Urada et al., 2010). The network analysis was conducted in UCINET version 6.374, a network analysis software program that calculates quantitative measures of network structure (Borgatti et al., 2002).

2.3. Measures

2.3.1 Dependent variable—The dependent variable was readmission to one or more detox programs within 1 year after discharge from the initial detox service. A 1-year observation period is common in SUD treatment outcomes research and has been used to evaluate detox readmissions in prior research (Mark et al., 2006). For each patient, a cut-off date equal to 365 days after the discharge from the initial detox service was established. If the date of the subsequent detox admissions fell before the cut-off date, the patient was coded as having a readmission. No distinctions were made between types of detox programs (e.g., residential or outpatient) or the number of days until the next detox service.

2.3.2 Independent variable—The presence of structural holes is operationalized with a measure known in network analysis as “efficiency.” Efficiency is the proportion of an actor's ties that are non-redundant (Hanneman and Riddle, 2005). Efficiency is calculated by first determining the effective size of a detox program's network, which is the number of ties a detox program has to other programs minus the average number of ties the detox program's contacts have with one another, not including their ties to the detox program (Hanneman and Riddle, 2005). For example, in Figure 1, Program A is the index program and has three ties to Programs B, C, and D. To count the number of ties the other programs have, one does not include their ties to the index program. Therefore, Program B has one tie. Program C has one tie. Program D has zero ties. The average number of ties for programs B, C, and D is .67 (2 ties/3 programs). The effective size of Program A's network, then, is $3 - 0.67$, or 2.33. Finally, efficiency is the effective size relative to the actual size of the network. The efficiency score for Program A would be $2.33/3$ or .78. By comparison, Program B's efficiency is .25 because its 2 ties are both connected, creating redundancy. However, Program B does gain efficiency from the fact that its neighbor, Program A, has a non-redundant tie with Program D.

Nine detox programs were excluded from the analysis because they either had no ties ($n=4$) or had only 1 tie ($n=5$). Networks consist of at least three actors; a set of two actors is a dyad. Therefore, the efficiency measure was not relevant for these nine programs. While it is not entirely clear why some detox programs have no ties and others have only one tie, one common characteristic of these nine programs is a small number of detox admissions.

2.3.3. Covariates—Out-degree is a network analysis measure that represents the number of patient transfers leaving a detox program for any other program, regardless of the type of program. Out-degree is an indicator of program size as it is strongly correlated with the number of admissions in this study. It is important to control for size because larger detox programs may have more opportunities for patient transfers due to their high volume.

Patient-level covariates were chosen for the analysis using the Anderson model of health services utilization (Anderson, 1995). According to the Andersen model, predictors of health services utilization can be categorized as predisposing factors (e.g., biology, socioeconomic status, living conditions), enabling factors (e.g., employment, health insurance), and factors related to one's current illness level (e.g., substance use disorder, mental illness).

Predisposing factors included in the model were sex, age (under 31, 31–41, 42–48, and 49

or older); race (Black, White, or other); Hispanic ethnicity (self-identified Cuban, Mexican, Mexican American, Puerto Rican, or other Hispanic/Latino); number of years of education; primary drug; and current living situation (homeless, dependent living, independent living). With respect to race, approximately 76.5% of the sample was either Black or White. Individuals from other racial groups (e.g., American Indian/Alaskan Native, Asian, and other racial/ethnic backgrounds) were coded as “other” because the subsamples were too small to analyze them separately. Homeless was defined as having no permanent residence. A dependent living situation was defined as living in a supervised setting such as a residential institution, jail, halfway house, or living with one's parents or relatives. Independent living was defined as owning a home, renting an apartment, or any other situation in which one paid rent and was not under supervision. Primary drug use was measured as a categorical variable consisting of the four most common drugs encountered in detox: heroin, alcohol, methamphetamine, and cocaine. A fifth category, “other drug”, was created for other drugs such as cannabis, other opioids, and psychedelic drugs.

Enabling factors included individual characteristics that may facilitate entry into SUD treatment, as well as actual transfers into treatment. Enabling factors included current employment (unemployed, working full- or part-time); criminal justice involvement (no criminal justice involvement, on parole, on probation, or other, e.g., in a jail diversion program, incarcerated, or awaiting trial); Medi-Cal coverage (California's Medicaid health care program); and continuity of service from detox to either residential or outpatient SUD treatment within 14 days of discharge from detox (“detox-to-treatment”). The “detox-to-treatment” measure indicates whether a patient was admitted to a residential or outpatient SUD treatment program. Length of stay in SUD treatment and quality of care were not measured in the current study. The distribution of patient transfers from detox was as follows: 24.3% of patients transferred to another detox program, 17.4% transferred to a residential program, 8.8% transferred to an outpatient program, and 50.5% received no additional care within 14 days of discharge (see Figure 2).

Current illness level factors included items associated with addiction severity, mental illness, and medical problems. Addiction severity was captured by the following measures: frequency of primary drug use, age of onset of primary drug, and prior treatment episodes. Frequency of primary drug use was defined as the number of days a patient reported using their primary drug in the 30 days prior to admission. Frequency of use is commonly used as a proxy for addiction severity and has good test-retest reliability as an individual measure and as part of the Addiction Severity Index summary measures (McLellan et al., 1980). Prior treatment was a binary measure indicating one or more treatment episodes during each participant's lifetime. The majority of patients (63%) had no prior treatment or one prior episode; therefore, the original continuous measure was dichotomized at one episode. Measures of mental and physical health were also binary measures. The mental illness measure is defined in CalOMS as having ever been diagnosed with a mental illness. The medical problems measure was defined as reporting at least one day of physical health problems during the 30 days prior to admission.

2.4. Statistical analysis

To test the hypothesis that network structure affects patient outcomes, a binary mixed model was conducted. The analysis had two levels: the patient and the detox program. Patients were grouped by their initial detox program. The regression analysis included a random intercept to account for the multilevel structure of the data and to obtain more accurate estimates of standard errors (Blakely and Woodward, 2000). In addition, a random effect was added to the coefficient for detox-to-treatment because this transition was assumed to vary within programs based on circumstances of the programs and patients. Maximum likelihood estimation in multivariate regressions was used to effectively respond to missing data for patient-level variables, which was approximately 4% in this sample. Maximum likelihood is considered the most adequate way to obtain unbiased estimation parameters (Allison, 2001). The xtmelogit procedure in Stata version 11 was used for this analysis (StataCorp, 2009). Statistical significance was determined by an alpha criterion of 0.01.

3. RESULTS

3.1. Sample characteristics

Table 1 summarizes patient sociodemographics, severity, and treatment history. Seventy-percent of detox patients were men. The sample was highly diverse in terms of age; the mean age was 40 years, but patients ranged in age from 14 to 83 years. The largest racial/ethnic groups were White, Hispanic, and Black. The rate of either full- or part-time employment was less than 20%. Patients reported a mean of 2.7 prior treatment episodes; however, the median number of prior episodes was 1. The readmission rate for patients in residential detox programs was 24.5%.

3.2. Residential detox networks

A total of 48 residential detox programs (84.2%) had ties to other programs based on patient transfers. The average number of ties based on out-going patient transfers or out-degree was 12.4 ($SD = 12$). The mean efficiency score was .68, which means that, on average, 68% of detox programs' ties were non-redundant, meaning they can create structural holes in the network ($SD = .25$).

3.3 Predictors of Detox Readmission

3.3.1 Network efficiency—Network efficiency was significantly associated with readmission; that is, higher efficiency was associated with lower odds of readmission for patients (log odds = -.02). Therefore, for every 10-point percentage increase in a detox program's efficiency, patient odds of readmission decreased by 18% (i.e., $1 - e^{10 * -.02}$). Out-degree or the number of outgoing patient transfers was associated with higher odds of readmission; that is, with every additional outgoing tie, the log odds of readmission increased by .03. Results from the mixed model are shown in Table 2.

3.3.2 Patient-level predisposing, enabling, and current illness level factors—Several predisposing factors were significantly associated with readmission in the mixed model. The odds of readmission among Blacks were approximately 17% higher than among Whites (95% CI = 1.04, 1.31). As a group, patients with American Indian/Alaskan Native,

Asian, and other racial/ethnic backgrounds had lower odds of readmission compared with Whites. Heroin users had higher odds of a detox readmission compared with patients with alcohol, methamphetamine, cocaine, and other opiate drug use disorders. Patients that reported having an independent living situation, i.e., having their own place to live, either an apartment or a house, had 0.79 times the odds of readmission compared with individuals that were homeless (95% CI = 0.71, 0.88). Patients in a dependent living situation also had lower odds of readmission compared with homeless patients, but the difference was not significant (OR=.91, 95% CI = .83, 1.01).

Enabling factors also predicted patients' odds of readmission. Continuity of service from detox to SUD treatment significantly reduced patient odds of readmission. Patients who transitioned from detox to either residential or outpatient SUD treatment had .44 times the odds of readmission compared with patients who did not transition to SUD treatment (OR=0.44, 95% CI= 0.34, 0.57). With respect to current illness level factors, the only significant predictor was having had prior treatment, which increased one's odds of readmission (OR=1.71, 95% CI=1.56, 1.87). Results of all patient-level predictors are presented in Table 2.

4. DISCUSSION

The high cost of detox services and health risks associated with continued substance use make readmission to detox an important indicator of poor performance for SUD treatment systems. This was the first study to examine the effect of interorganizational networks on a SUD treatment outcome. The impact of interorganizational networks on patient outcomes has been studied in the mental health services field (Heflinger, 1996; Morrissey et al., 1997; Provan et al., 2009) and in the area of HIV prevention (Thomas et al., 2007). This study helps to bring a broader ecological perspective to the field of addiction health services research.

This study tested structural hole theory by incorporating a measure of non-redundant ties (network efficiency) in a multilevel analysis of readmissions to detox. The hypothesis that greater network efficiency is associated with lower odds of readmission was supported. After controlling for multiple patient-level characteristics and continuity of service, network structure had an independent effect on detox readmission. This finding suggests that there are advantages to operating within networks with fewer non-redundant ties. Less redundancy could imply access to a broader set of referral resources than what is immediately available in a detox program's network. However, future research is needed to test whether interorganizational ties based on patient transfers represent actual referral relationships.

This study found a small positive effect of out-degree on the odds of readmission, which implies that as the number of network ties increases, so do the odds of readmission. Research in the systems integration field has suggested that larger networks may be harder to coordinate, considering the time and effort it takes to develop relationships across programs and organizations (Provan and Milward, 1995). This finding also relates to other

studies on detox readmissions that found larger programs, based on number of beds, had higher rates of readmissions (Callaghan and Cunningham, 2002; Campbell et al., 2010).

One major service gap in the continuum of care for substance use disorders associated with readmissions is not transitioning patients to SUD treatment after providing detox services (Mark et al., 2006; McLellan et al., 2005). This study found that continuity of service from detox to either residential or outpatient SUD treatment was associated with a significant reduction in the odds of readmission. It is possible that detox programs with higher efficiency in their networks more effectively transition patients into SUD treatment. In order to fully understand the advantages of network efficiency for patient outcomes, future research should include mediational analyses to examine whether continuity of service after detox mediates the association between network efficiency and detox readmissions.

4.1. Strengths and limitations

Interorganizational networks have received very little attention in addiction health services research. This study helped to fill this gap and bring a broader ecological perspective to the field. This was the first study to use patient transfers to construct interorganizational networks in the SUD treatment sector. It is clear from the patient transfer data that treatment programs are embedded in interorganizational networks. Programs may or may not be aware of all of their organizational ties or exploit them to enhance their service capacity, but these ties represent social systems that affect treatment outcomes. This study's findings suggest that performance indicators for SUD treatment such as the ones recommended by the Washington Circle can also be used to evaluate performance of treatment systems in addition to individual programs or organizations (Garnick et al., 2009).

The present study was the first to examine the influence of interorganizational networks on detox readmissions. This study was also the first to use measures from social network analysis as predictors of SUD treatment outcomes. The present study makes a significant contribution to the SUD treatment literature because data were analyzed for a large detox patient population from diverse racial/ethnic backgrounds. Finally, although this study examined systems integration within the drug treatment sector, the concepts and methods used are applicable to systems integration research in other health-related fields.

The study findings must be understood within the context of several limitations. First, the patient transfer networks only captured exchanges between programs within the publicly funded SUD treatment sector. Gaining a complete picture of referral networks would require the inclusion of other health care services, mental health services, and housing services, as well as self-help groups, sober living homes, and other recovery support services. It is possible that many of the patients that did not receive SUD treatment after detox received supportive services through informal channels such as self-help groups, e.g., Alcoholics Anonymous. Because CalOMS does not capture referrals to services outside the formal treatment sector, future research may need to include surveys to collect network data. Second, only 32 of the 56 counties in California reported detox admissions data to CalOMS. The reasons for the lack of detox admissions data in the other 23 counties are unclear as this information was not available.

The third main limitation has to do with the reliability of administrative data. Administrative data may not be collected in a uniform, systematic way across counties. Differences in the reporting of detox admissions have been uncovered in recent evaluations of CalOMS (Urada et al., 2010). In addition, data from referral-related questions asked at admission and discharge may be of limited value because treatment programs may not provide analogous answers.

Finally, CalOMS data may have limited value for estimating the effect of patient severity on detox readmissions or other performance outcomes. CalOMS does not include diagnostic data on substance abuse and mental health, which would provide direct measures of patient severity. The current questions related to having medical problems or having a lifetime mental illness diagnosis are imprecise and may not capture varying levels of severity among patients. The ability to estimate the effects of patient diagnoses on treatment performance is a critical issue for evaluation of treatment programs (Federman et al., 2000).

Although administrative data have many limitations, there are also advantages. Administrative data can be used to examine interactions between patients and service delivery systems. Because these data are collected on an ongoing basis, service access and utilization can be examined over time (Evans et al., 2010). With respect to network analysis, administrative data have an advantage over survey data in that interorganizational ties are observed from a patient-flow perspective. Self-reports of organizational ties are subject to a variety of respondent biases, including recall bias, reporting bias, and social desirability bias. Patient-level data allow researchers to construct service networks from the ground up, as opposed to reports from program administrators who may or may not have adequate information about service-level linkages.

4.2. Implications

In the context of drug abuse treatment, having fewer redundant ties may represent a certain capacity within detox programs to respond to patients' diverse needs and preferences for rehabilitation care. The placement of patients into SUD treatment after detox services can be complicated. In addition to a patient's preference for treatment, there is the issue of limited availability of treatment, particularly in the case of residential treatment. Additional complexity arises when a patient lacks stable housing, has a co-occurring mental health disorder, or does not have coverage through Medi-Cal. Greater access to diverse programs through non-redundant ties may facilitate the transfer of detox patients to SUD treatment. Future research is needed to understand the types of services accessible to patients through detox program networks and the effectiveness of those services in reducing readmissions to detox.

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Figure 1.
Illustration of ties between Programs A, B, C and D.

Figure 2.
Distribution of Patient Transfers from Residential Detox Programs, CalOMS 2008–2009 ($N = 18,278$)

Table 1Characteristics of patients in residential detox programs, CalOMS 2008–2009 ($N = 18,278$)

Variable	% or M (SD)
Male	70.6
Race	
Black	18.8
White	60.4
Other	20.7
Hispanic	21.8
Age	
14–30	24.0
31–41	27.6
42–48	24.2
49+	24.2
Employed	10.6
Criminal justice involvement	
None	71.0
Parole	9.2
Probation	19.0
Incarcerated	1.0
High school education	73.6
Living situation	
Homeless	46.5
Dependent living	30.1
Independent living	23.5
Medi-Cal beneficiary	18.3
Primary drug problem	
Heroin	18.0
Alcohol	42.5
Methamphetamine	30.8
Other (e.g., other opiates)	8.7
Addiction severity	
Received prior treatment	58.0
Days of primary drug use during previous 30 days	21.6 (11)
Lifetime mental illness diagnosis	27.7
Medical problems during previous 30 days	27.0
Treatment	
Transfer from detox to treatment	26.2
Readmission to detox within 1 year	24.5

Table 2

Results of a binary mixed model predicting readmission to residential detox programs, CalOMS 2008–2009
($N = 18,278$)^a

Fixed Effects	B	SE	OR	95% CI
Detox networks ($n = 48$)				
Efficiency	-.02	.01	0.98	0.97, 0.99 *
Out-degree	.03	.01	1.03	1.02, 1.04 *
Predisposing factors				
Male vs. female	.23	.05	1.26	1.15, 1.38 *
Age				
31–41 vs. 14–30	.11	.06	1.12	1.0, 1.25
42–48 vs. 14–30	.12	.06	1.12	0.99, 1.26
49+ vs. 14–30	.03	.06	1.03	0.92, 1.17
Race				
Black vs. White	.16	.06	1.17	1.04, 1.31 *
Other vs. White	-.19	.07	0.82	0.72, 0.94 *
Hispanic ethnicity vs. not	.08	.07	1.08	.95, 1.23
Education (years)	.02	.01	1.02	1.0, 1.04
Living situation				
Dependent living vs. homeless	-.09	.05	0.91	0.83, 1.01
Independent living vs. homeless	-.24	.06	0.79	0.71, 0.88 *
Primary drug problem				
Alcohol vs. heroin	-.43	.06	0.65	0.58, 0.73 *
Methamphetamine vs. heroin	-.58	.07	0.56	0.49, 0.65 *
Cocaine vs. heroin	-.35	.08	0.71	0.61, 0.82 *
Other drugs vs. heroin	-.63	.09	0.53	0.45, 0.63 *
Enabling factors				
Employed vs. unemployed	-.27	.07	0.80	0.69, 0.92 *
Criminal justice involvement				
Parole vs. none	-.01	.07	0.99	0.86, 1.13
Probation vs. none	-.07	.06	0.93	0.84, 1.04
Incarcerated vs. none	-.09	.24	0.92	0.57, 1.47
Transfer detox-to-treatment vs. not	-.81	.13	0.44	0.34, 0.57 *
Medi-Cal beneficiary vs. not	.05	.05	1.05	0.95, 1.16
Current illness level factors				
Addiction severity				
Prior treatment vs. none	.53	.05	1.71	1.56, 1.87 *
Days of primary drug use during previous 30 days	.005	< .01	1.00	1.0, 1.01

Fixed Effects	B	SE	OR	95% CI
Lifetime mental illness diagnosis vs. none	.09	.05	1.09	1.0, 1.20
Medical problems during previous 30 days	.07	.05	1.07	0.98, 1.18
Prior treatment vs. none	.53	.05	1.71	1.56, 1.87 *

Random Effects	EV	SE	95% CI
Transfer detox-to-treatment	.23	.05	.15, .36
Model fit: $\chi^2 = 467.18$, $df = 27$, $p < .001$			

^a The sample was reduced to 17,484 cases due to missing data. Only significant predictors from the initial logistic regression were included in this model. EV = estimated variance.

* $p < .01$