Positive and Negative Support Roles in the Social Networks of Vulnerable People

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Thesis Abstract

Introduction: Social networks have shown promise in curbing drug dependency and infectious diseases among marginalized populations. The purpose of this study is to elucidate how relationship strength in social networks is associated with risk behaviours for infectious diseases.

Methods: Two reviews were conducted: 1) a systematic review exploring the association between risk behaviours and relationship strength 2) a review on the utilization of respondent driven sampling (RDS). We also analyzed network data to determine the association between recent injection drug use and recent crack use.

Results: Our reviews revealed that few studies link relationship strength and risk behaviours; moreover, RDS is effective method of sampling from marginalized populations. Finally, our analysis demonstrated that close relationships are associated with drug use.

Conclusion: “Close” relationships are important in arbitrating injection drug use and crack smoking. More research addressing the issues of using data from dynamic social processes and hard-to-reach populations is needed.

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Introduction

Street-involved persons, sex workers, and people who smoke crack or inject drugs face a myriad of both physical and mental health challenges. Studies have shown that these groups experience higher rates of addiction (1, 2), substance dependence (3, 4) , depression (5, 6) and anxiety (7, 8) than the general population. They also carry a large burden of infectious comorbodities including TB, Hepatitis C (9, 10), sexually transmitted infections (STIs), and HIV (9, 11, 12). These challenges often stem from and are exacerbated by issues such as low income, unstable housing, unemployment and crime, which push street-involved and drug-using individuals into social exclusion and marginalization (13, 14).

Despite the tools available to preserve health among marginalized populations, STIs and bloodborne infections continue to be endemic. Since the discovery of HIV/AIDS, drug cessation and condom promotion programs have been at the forefront of public health efforts (15). The 1990s saw a number of public health domains begin to adopt the harm reduction approach, which encourages the use of condoms, clean needles, and less invasive forms of drug uptake (16). However, research has shown that the adoption of these behaviours still remains relatively low and inconsistent in this population, and health denigrating behaviours continue to flourish (17-19). It is clear that public health is in need of extra tools that can help marginalised individuals move toward more health preserving choices.

Macro level approaches, which shift the focus from the individual to the greater social environment, have shown promise in enabling this change (20). Research has shown that the social environment is independently associated with illness and mortality, over and above individual risk factors (21). Most contemporary health frameworks enlist the social environment as an important determinant of health (22). A large component of the social environment is the social network, which consists of a set of individuals and the relationships between them. In social network terminology, each individual in the network (20) is known as a node, and the relationship between nodes are called ties (23). For example a person who uses drugs and all of their contacts—including their friends, their family and their drug-using peers—consists of a social network. Networks centered around one individual are called egocentric and networks that illustrate the full set of ties within a community are called sociocentric (23). Capturing every relationship within a community is difficult, if not impossible, to achieve among communities that are large or that experience any type of migration (23). Thus, most social network research focuses on egocentric networks.

Social network analysis concerns itself with ascertaining the properties of social networks and is gaining momentum in various disciplines including biology, anthropology, economics, information science and organizational studies (23). Scientists are interested in network properties such as the structure of the network and the nature of the ties. Ties within any network can vary in function and quality. For example, a tie may be a friendship that is considered “close”. The ties in an individual’s life can have a profound impact on the way an individual thinks and behaves. One way of characterizing ties is through tie strength, a term coined by Granovetter (24). According to Granovetter, tie strength is characterized by a linear combination of time, emotional intensity, intimacy and reciprocity (24). Time refers to duration of the relationship, intimacy refers to the ability to confide in one another, and reciprocity refers to mutual exchange within the relationship (24). Emotional intensity refers to the magnitude of emotional connection, which is often measured by one’s perception of “closeness” to another individual (24). Multiplexity is also another social network term that has been associated with tie strength, and refers to an overlap in roles (25, 26). For example, a social contact who is a friend and a work colleague has a multiplexity score of 2. Sociologists and organizational scientists have been interested in tie strength for information diffusion and labor relations (27, 28).

Krackhardt argued that strong ties are of importance during times of change and ambiguity (29). He argues that strong ties “constitute a base of trust that can reduce resistance and provide comfort in the face of uncertainty” (29). This may be especially true for marginalized populations, who often face unstable housing and precarious employment. Berkman and Glass asserted that social networks provide opportunities for psychosocial mechanisms such as social support and peer influence to occur, which impacts health through either health promoting or health disparaging behaviours (30). Wellman and Wortley demonstrated that strong ties give rise to emotional aid, small services, and companionship (31). In the context of vulnerable populations, small services such as getting a ride to an appointment and receiving emotional support can be crucial in the everyday struggles of coping with addiction and living on the streets.

The support that strong ties provide in relation to an individual’s drug and risk behaviors has received little attention. There is only a handful of empirical evidence that explores the association between the presence of strong ties in a marginalized person’s life and their health behaviours. Other aspects of social networks, such as the structure, density, and geographic distance between nodes, have been shown to be associated with drug behaviours (32). For example, Latkin et al. found among drug users in Baltimore, injecting with used needles was associated with having a larger drug network and more connections within one’s personal network (also known as greater “density”) (33). Moreover, among high-risk individuals in Colorado Springs, Rothenberg found that when the number of connections within one's personal network declines over time, needle sharing also decreases (34). Wylie et al. illustrated the geographic organization of hotels identified by injection drug users as a place for injection, which reveals areas where harm reduction interventions are needed (35). Capturing the underlying structure and characteristics of the network can reveal not only how the disease spreads, but also how the adoption of health-protective behaviours arises in this population.

Evidence demonstrating the link between risk behaviours and the quality of relationships in the social networks of vulnerable people is less clear. One reason for this lack of evidence is the nature of sampling from vulnerable populations. Since their activities are illegal and highly stigmatised, sex workers and people who use drugs hide their behaviour from governments, law enforcers, and even family and friends. As a result these individuals are 'hard to reach' and traditional random sampling techniques, such as the creation of a sampling frame, are impossible (36). Different methods have been proposed to overcome this problem (37, 38), but one of the most successful techniques is called Respondent Driven Sampling, which takes advantage of vulnerable peoples' social networks to reach even the most hidden members of this community (36). It is important to review the literature of methods for sampling hidden populations in order to better inform research in this area.

This research seeks to provide empirical evidence on whether or not an association exists between strong ties and risk behaviours for infectious diseases. It also seeks to explore the issues surrounding the sampling of marginalised and hidden populations to bring up to date the best strategies available for the collection of this data. In doing so, we hope to contribute to the ever-growing literature on social networks and their importance in mitigating illness among vulnerable populations.

1.1 Rationale

To date, the quality of relationships in the social networks of marginalized populations has been given little attention. Relationships, especially those that have high levels of trust and involvement, have been shown to confer a high level of peer influence and social support (30). This, in turn affects health through health behaviours (39). It follows that the strong ties of marginalized people may have the power to influence risk behaviours, including drug use, needle behaviours, and condom use. Understanding this relationship can help bolster current interventions aimed at reducing infectious diseases and addiction within this population.

In the recent decade, a variety of papers have arisen about using respondent-driven sampling as a method of collecting data from hidden or hard-to-reach populations (40-43). The literature has stressed its advantages over previous techniques and presented several methods on how to statistically adjust for the non-random nature of the data (36). However, to date, no paper has compiled this information for use in epidemiological research. As a result, researchers may be unclear as to the existence of respondent driven sampling and how to treat the corresponding data. It is important to elucidate this in order to stimulate research among extremely hidden populations that could benefit from representation in the health literature.

1.2 Objectives

The overall objective of this paper is to elucidate how strong ties in the social networks of vulnerable people are associated with drug and HIV risk behaviours.

Specific objectives include:

1. To determine the state of evidence regarding the association between strong ties and risk behaviours of vulnerable people.
2. To compare methods of sampling hard-to-reach populations and contrast different approaches to analyzing respondent driven sampling data.
3. To identify associations between drug behaviours and multiplexity, tie strength, and closeness in the social networks of vulnerable people in Ottawa, Ontario.

1.3 Chapter summaries

Chapter One: Relationship Quality

The primary goal of this research was to identify if an association existed between risk behaviours and social network tie strength measures among vulnerable populations. This chapter consists of a systematic review of the literature relating condom use, injection drug use, and needle sharing with three measures of tie strength. We hypothesized that an individual's risk of engaging in health compromising behaviours will increase when their social network has strong ties with persons who also engage in risk behaviours, but will decrease when their social network has strong ties with persons who do not participate in such activities. The scientific literature relating tie strength to risk behaviours was reviewed and integrated. We found that few studies sought to examine this relationship and thus no association could be firmly established. Moreover, few studies differentiated between risk-taking and non-risk-taking social network members. We also acknowledge the difficulty in obtaining "valid" measures from vulnerable people, who are difficult to capture methodologically, and social networks, which are dynamic processes. We highlight the need for more research not only relating tie strength to risk behaviours, but research exploring the methodological issues at hand.

Chapter Two: Challenges and Successes in the Design and Analysis of Respondent Driven Sampling for Hidden Populations: A Review of Current Methodology

One of the objectives of this research was to identify what strategies exist for sampling hard to reach populations and explore their limitations. One of the current ways of gathering data from such populations is a method called respondent driven sampling (RDS), which uses respondents to recruit future participants. Each respondent is given a set number of recruitment coupons to distribute to their contacts; when one of their recruits participates in the study, they too are given a set of coupons. The coupons are tracked and enable researchers to study the pattern of recruitment. There has been ongoing debate on how to best analyze respondent driven sampling data since it comes from a non-probability sample. In turn, many assumptions are violated when performing traditional statistical analyses. This chapter presents a review of the strengths and limitations of current methods of sampling hard to reach populations with a focus on respondent Driven sampling. Moreover, it summarizes the latest statistical techniques suggested to account for the non-random nature of a respondent driven sample. In this chapter, we argue that RDS avoids the severe selection biases presented by other methods, however, methods for correcting for the non-probability sample need to be further developed.

Chapter Three: Supportive Strong Ties and their Association with Drug Use

This chapter consists of the third and final manuscript of this research investigating tie strength measures and risk behaviours. It consists of a primary analysis of data collected from sex workers, homeless individuals, and people who use drugs in Ottawa, Canada. Two outcomes were investigated: crack use in the last 6 months and injection drug use in the last 6 months. The exposure variables were closeness, relationship duration, and multiplexity. Logistic regression models were used to explore these relationships. This research contributes new insights on how having strong-tie support network members can promote health-protective behaviours.

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HIV risk behaviours and strong ties in the social networks of vulnerable people: a systematic review

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Chapter One: HIV risk behaviours and strong ties in the social networks of vulnerable people: a systematic review

The primary goal of this research was to identify if an association existed between risk behaviours and social network tie strength measures among vulnerable populations. This chapter consists of a systematic review of the literature relating condom use, injection drug use, and needle sharing with three measures of tie strength. We hypothesized that an individual's risk of engaging in health compromising behaviours will increase when their social network has strong ties with persons who also engage in risk behaviours, but will decrease when their social network has strong ties with persons who do not participate in such activities. The scientific literature relating tie strength to risk behaviours was reviewed and integrated. We found that few studies sought to examine this relationship and thus no association could be firmly established. Moreover, few studies differentiated between risk-taking and non risk-taking social network members. We also acknowledge the difficulty in obtaining "valid" measures from vulnerable people, who are difficult to capture methodologically, and social networks, which are dynamic processes. We highlight the need for more research not only relating tie strength to risk behaviours, but research exploring the methodological issues at hand.

HIV risk behaviours and strong ties in the social networks of vulnerable people: a systematic review

Introduction

Street involved individuals, sex workers, and people who inject drugs or smoke crack represent a difficult to reach population with respect to prevention of illness and treatment (1). As a result of this and their risk activities, this population experiences disproportionately high rates of bloodborne diseases and sexually transmitted infections (2-5). Interventions such as testing, treatment, condom use, harm reduction, and drug prevention have shown moderate success but there is a need for more tools to increase uptake and enable sustained, positive changes in behaviour (6). One such tool includes a person's social network, which consists of the relationships they have with other individuals (7). These connections directly impact behaviour and naturally exist in most peoples' lives, making them a valuable path for health promotion beyond the hands of health professionals and institutions.

It is important to understand the nature of these relationships to better inform how they can be used to halt the spread of infectious diseases among socially disadvantaged and marginalized populations. In particular, relationships considered "strong" may have a powerful influence on whether one decides to partake in health denigrating behaviours, such as doing drugs and sharing needles, or health promoting behaviours such as condom use. According to Granovetter, relationship strength, or "tie strength" can be characterised using three measures: 1) emotional intensity, 2) multiplexity and 3) duration of the relationship (8). Emotional intensity describes a perceptual feeling of connection, sometimes measured in the literature as 'closeness' (8). Multiplexity describes the number of roles played by a social network member—the more roles they play (for example, spouse, drug dealer, neighbour), the higher the strength of the relationship (9). Finally, relationships that extend for a long period of time are indicators of high strength relationships (8).

We hypothesize that a person's drug use, drug equipment sharing and condom use is associated with the presence of strong tie relationships in their lives. However, this association is mediated by whether these network members also partake in these behaviours. In other words, we hypothesize that a person who has very close, long-term, or multiplex relationships with individuals who inject, share needles, or participate in unsafe sex is more likely to also engage in these behaviours.

However, persons who have strong relationships with individuals who do not participate in drug injection, needle sharing, or unsafe sex are more likely to refrain from such activities.

Here, we searched the literature to see if there exists enough evidence to show that long-term, multiplex and perceptually close relationships are associated with risk behaviours among people who use drugs, street-involved individuals, and sex workers. In particular, the risk behaviours of interest were drug/alcohol use, drug equipment sharing, and condom use. Because we wished to see the effect of any strong tie in the relationship, rather than being limited to particular roles (such as the effect of close mothers, close spouses, etc.), only studies that evaluated the whole social network were considered. We conducted a systematic review to compile the best available evidence in the literature.

Methods

We aimed to identify all social network studies investigating the relationship between tie strength and risk behaviours up to October 2012. All titles and abstracts were screened by two reviewers (MA and KA) independently and in duplicate. Disagreements were resolved by consensus.

Data sources

A librarian specializing in epidemiological research (LS) and the primary investigator (MA) formulated a search strategy together for study selection. The following databases were searched: EMBASE (conception to October 2012), MEDLINE (conception to October 2012), PsycINFO (conception to October 2012), CINAHL (January 1981 to October 2012), and Sociological Abstracts (conception to October 2012). Abstracts, non-published studies, and articles in languages other than English were not considered.

Study selection

The population of interest was street-involved individuals, sex workers, and people who use drugs. Only individuals over the age of 12 were considered. We were interested in the social network characteristic of tie strength and its impact on risk behaviours. We anticipated that included studies may measure tie strength in a variety of ways; comparisons may have involved those who had strong tie members in their network versus those who did not, or comparing frequencies of tie strength members in the network, The outcomes of interest were drug-related behaviours, including drug use and equipment sharing, as well as condom use. Controlled vocabulary and keywords were used for the following terms: *social networks, relationship quality, closeness, multiplexity, relationship duration, drug use, prostitution,* and *homelessness.*

Eligible studies were cross sectional, case control, cohort and randomized controlled trials which examined the effect of closeness, multiplexity, or relationship duration on drug behaviours and condom use. Only studies which used social network analysis were considered since we wished to examine the effect of *any* strong-tie relationship rather than role-specific ones (e.g. studies only looking at strong relationships with mothers).

Data extraction

MA used a standardized form to extract data from each study. The quality of relevant studies was assessed according to the validity and completeness of exposure and outcome ascertainment and comparability of the control group.

Data synthesis

The differences in measurement of social networks, tie strength, and various outcomes made formal meta-analysis impossible. Thus, we used a method of grouping results developed by Ramirez et al. (10) and used by others (11). Results from studies that adjusted for confounding variables in a multivariate analysis were presented (Table 3). Each effect estimate was grouped into one of three categories: 1) an inverse relation between tie strength and risk behaviour at the 5% level (longer relationships, higher multiplexity, and greater closeness associated with a lower risk of performing behaviour) 2) no evidence of an association (estimate not significant at the 5% level) and 3) a positive association between tie strength and risk behaviour (high levels of tie strength associated with high risk of performing behaviour). We counted the number of studies for each exposure and outcome combination, and aggregated the sample sizes. Each combination yielded only a low number of studies, which precluded any sensitivity testing.

Results

Literature search

Figure 1 outlines the study selection process. Out of 123 titles and abstracts, 10 met all inclusion criteria. This included 3 cohort studies and 7 cross-sectional studies.

Characteristics of included studies

We outlined the characteristics of included articles in Table 1. All were published between 1994 and 2011. All studies except for one (12) were conducted in North America. Most used a combination of outreach, targeted, and snowball sampling to recruit from their target population. No study used random sampling techniques. Only cross-sectional and cohort studies were identified.

Although all studies used a social network inventory, questions used to define the network varied among the studies (Table 2). Most studies elicited a variety of social contacts, including those with whom the participant had sex, "hung out", or used drugs. Among all studies, only one study separated drug-using contacts from non drug-using ones when looking at the relationship between tie strength and risk behaviours (13). No study explored the risk behaviour of social network members as a possible mediator between tie strength and drug use, drug equipment sharing, or condom use.

Five studies examined needle or equipment sharing as the outcome (12-16). Only one study used a validated assessment tool for drug use, which was the ASI tool for drug use (17). Only two studies looked at the effect of tie strength on condom use (18, 19), and two studies integrated condom use, drug use, and drug equipment sharing to create an index of HIV risk (20, 21).

Most studies were concerned with measures of emotional closeness as the exposure variables: only four studies investigated social network multiplexity (13, 17) or length of relationship (12, 20). Closeness was most often measured as a scale from 'not close at all' to 'very close'. However, some studies created their own measure of closeness, which included concepts such as affective strength, interactive intensity, trust, frequency of contact, and order named during the network elicitation component. Multiplexity was measured either as the average number of functions each network member played in the focal person's life, or the percentage of the network that was named in other networks (i.e. drug, sex, and friendship).

All studies had a number of methodological limitations. A primary limitation was that a cross-sectional design was used for all but three of these studies (two of which were principally descriptive). This makes the direction of association between tie strength and risk behaviours impossible to determine. It is very possible that the more a person engages in risk behaviours, the less "strong" their relationships become. Other common limitations were lack of random sampling, and limited generalizability due to inclusion criteria.

Results of studies

The results of studies examining the association between tie strength and risk behaviours are summarized in Table 3. The number of studies exploring closeness, multiplexity or length of relationship and each outcome are few, which makes the assessment of associations between tie strength and risk behaviour outcomes problematic. Only one effect estimate, which demonstrated a null association, existed for the relationship between length of relationship and sharing needles (12). Multiplexity appeared to be positively associated with sharing needles among adolescent injection drug users in all three available effect estimates (13). Two effect estimates (16) showed that increasing closeness was associated with sharing needles, but five effect estimates (12, 16) found no association.

One study looked at the transition to injecting among non injection drug users, and found that closeness appeared to be inversely associated with the initiation of injecting (15). That is, the less close the non-injectors perceived themselves to be to their injecting social network members, the more likely they are to transition to injecting. The two studies exploring condom use found no association with closeness (18, 19).

One study (20) created a composite HIV risk score that encompassed both drug risk behaviours and condom behaviours. The authors found no association between the length of relationship and HIV risk score, and a significant positive relationship between closeness and HIV risk score.

Figure 1. Flow chart outlining the study selection process for the effect of tie strength (closeness, multiplexity and duration of relationship) on drug use, drug equipment sharing, and condom use

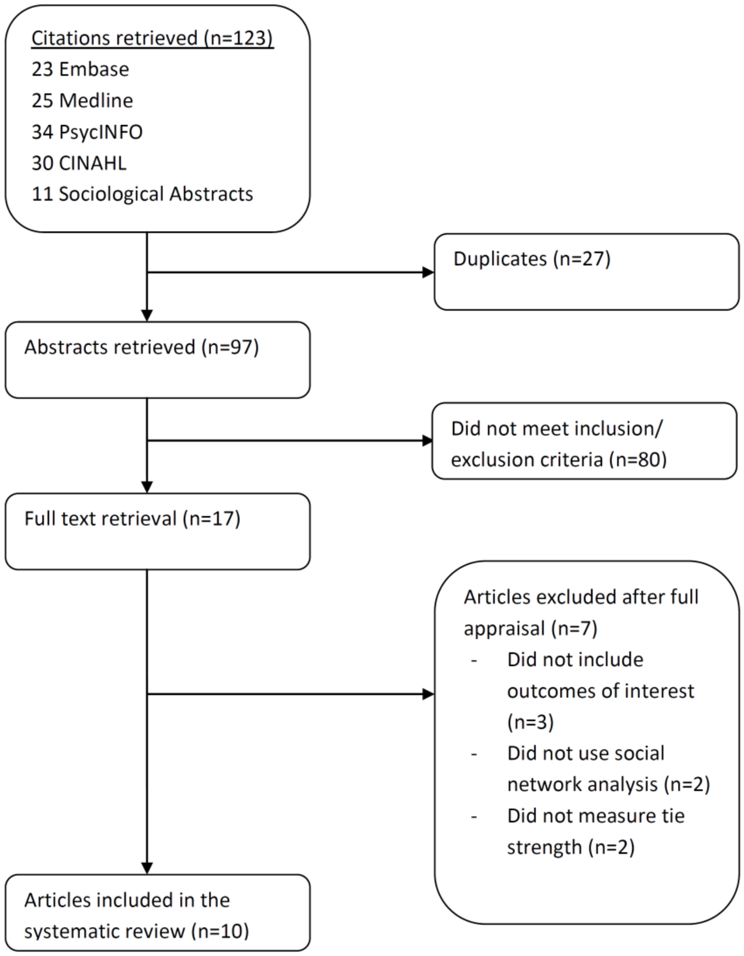

Table 1. Characteristics of included studies that have examined the effect of closeness, multiplexity, and relationship duration on drug use, drug equipment sharing, and condom use among vulnerable people

Study Design	Reference	Year	Country	Setting	N	Method of Recruitment
Cross-sectional	Bell et al.	2007	USA	Drug users and nonusers and their sexual and drug injection partners	267	Respondent driven sampling and two-step random walk method
Cross-sectional	Lakon et al.	2006	USA	Adolescent injection drug users	277	Snowball and purposive
Cross-sectional	Montoya et al.	1998	USA	Female injection drug users	60	Venue based and outreach.
Cross-sectional	Neaigus et al.	1994	USA	Injection drug users	1124	Street recruited
Cross-sectional	Neaigus et al.	2006	USA	Non injection drug users	579	Targeted sampling, street outreach, chain referral
Cross-sectional	Paquette et al.	2011	Australia	Injection drug users	261	Respondent driven sampling
Cohort (but cross-section results)	Rothenberg et al.	2005	USA	At-risk populations for HIV	595	Street outreach
Cross sectional	Tortu et al.	2000	USA	Female drug users	320	Targeted sampling
Cohort	Trumbetta et al.	1999	USA	Homeless persons diagnosed with substance abuse and severe mental illness	155	Psychiatric outpatients
Cohort	Valente & Vlahov	2001	USA	People who use a needle exchange program	1383	Every 7th person who visited the Baltimore Needle Exchange Program

Table 2. Quality of studies examining the effect of closeness, multiplexity, and relationship duration on drug use, drug equipment sharing, and condom use among vulnerable people.

Reference	**Determination of social network**	**Determination of drug use/ equipment sharing or condom use**	**Determination of closeness, multiplexity, and/ or relationship duration**	**Inclusion Criteria**	**Adjustment for confounding variables**
Bell et al.	30 day drug injection, sexual, and cocaine use partners, drug supplier contacts, and persons to whom participants were "close".	Conditional probability of HIV transmission, using a risk index.	Relationship duration: how long they had known each relationship partner. Closeness: A composite score of four items measuring trust, respect, caring for the partner, and telling the partner about "important things" and duration of years of the relationship.	1) Spend a lot of time in recruitment area 2) Cocaine, heroin or methamphetamine use >3 time a week 3) Injection track marks or positive urine test for heroin, cocaine or methamphetamines	Sex of partner, self protection, social norms, relationship closeness, power resources, gender power, drug use, race.
Lakon et al.	Individuals with whom participants injected drugs, had sex, or "hung out" within the past 30 days.	Risky needle use (yes/no)	Closeness: scale from 1 to 4 (1=not close at all; 4=very close) for each network member. Closeness was found as a mean. Multiplexity: the number of people named in the focal network who were also named in other networks, divided by the size of the focal network.	1) Injected drugs in the last 30 days 2) Female or male (not transgendered)	Gender, race, age, ethnicity, age at which respondents started using heroin, cocaine, or speed.
Montoya et al.	Persons to whom they felt "closest" to.	Condom use	Closeness: Connective score based on affective strength and interactive	1) Crack cocaine use in the last 30 days	Age, ethnicity, self efficacy.

			intensity	2) More than one male sex partner in the last 30 days.	
Neaigus et al. (1994)	Individuals considered their "social contacts", and persons with whom the subjects had injected with or shared needles with in the 6 months prior to interview	Drug injection and sharing needles with others.	Closeness: how often had contact with three closest friends.	1) 18 years of age or older 2) Not in treatment in the 30 days prior to the interview 3) Injected in the past 6 months	Closeness not included in multivariate model.
Neaigus et al. (2006)	Contacts in the prior 30 days; persons with whom they used drugs/ had sex OR to whom they would go for emotional/ material support.	Drug injection (intravenous, intramuscular, subcutaneous)	Closeness: emotionally "very close".	1) 18 years of age or older 2) Used non injected heroin in the last 30 days 3) Had never injected drugs OR (if former injector) had not inject in last 6 months	Crack, alcohol use in the past 30 days; age at first heroin use; age; ethnicity, fear of injecting with needles; friends believe it is "OK" to inject drugs; duration of heroin use, use >=2 bags of heroin per day, exposure to current IDUs.
Paquette et al.	Individuals whom they knew by name and who knew them by name, who injected drugs, who were over 18 years of age, and who resided in South East Sydney	Syringe and/or ancillary equipment sharing	Closeness: "close" friend/ sex partner/ family Duration of relationship: Known 0-5 years or >5 years.	1) 18 years of age or older 2) Injected an illicit substance in the previous month 3) Reside in Sydney	Aboriginal or Torres Strait Islander origin, age, testing for Hepatitis C in the previous year.
Rothenberg et al.	Network interview (sexual, social, drug using, and needle-sharing contacts)	Direct contacts to HIV	Closeness: scale from 1 to 10.	1) Exchange of sex for money or drugs 2) Sex with prostitute 3) Intravenous illicit drug use 4) Sex with an injecting drug user	N/A. Mainly descriptive.
Tortu et al.	Partners with whom they had sex.	Unprotected intercourse event	Closeness: Respondent's perceived closeness to	1) At least 18 years of age	N/A. Was not included in multiple regression.

			partner during event	2) Heterosexually active in last 6 months 3) Non-injected heroin, cocaine, crack use in the previous 30 days	
Trumbetta et al.	Persons whom provided support or service to the participant (Social Support and Social Network Interview, SSNI)	ASI instrument for drug use	Multiplexity: average number of functions performed by each social network member.	1) Age 18 to 50 2) 3 months residence in Washington 3) Diagnosis of severe mental illness 4) Psychoactive substance abuse or dependence 5) Homelessness	Bivariate and descriptive only.
Valente & Vlahov	5 of the participants closest friends.	Sharing syringes with close friend	Closeness: order named among close friends	None.	Sex, age, living in one's own residence, race/ethnicity, employment status, high drug use, sex for money or drugs, survey wave, surveys completed.

Table 3 Summary of data on the association between tie strength and risk behaviours

Outcome	Tie strength measure	Number of effect estimates (sample size)	Number of effect estimates (sample size)		
			Inverse	No Association	Positive Association
Sharing Needles	Length of relationship	1 (261)	0	1 (261)	0
	Closeness	7 (4542)	0	5 (3097)	2 (1445)
	Multiplexity	3 (729)	0	0	3 (277)
Transition to Injecting	Closeness	1 (160)	1 (160)	0	0
Condom Use	Closeness	2 (380)	0	2 (380)	0
HIV risk (summary score)	Length of relationship	1 (267)	0	1 (267)	0
	Closeness	1 (267)	0	0	1 (267)

*Only results of multivariate analyses are provided here.

*Alpha=0.05

Discussion

Not enough evidence exists to demonstrate that there is an association between closeness, multiplexity, or duration of relationship and drug use, drug equipment sharing and condom use. Studies are sparse in number, making it difficult to compare studies and draw conclusions. Three of the studies identified in this research only ascertained univariate associations and did not determine effect estimates (14, 17, 21). Moreover, studies that do exist raise concerns about validity, which are principally due to the nature of both social networks and the target population. We will explore potential explanations for the results and discuss the validity of the studies.

Two effect estimates (12, 16) found a positive association between closeness and sharing syringes, but five did not (13, 16). Misclassification of the closeness variable may explain the lack of consistency with regards to the direction of association. Among those that found an association, closeness was measured as the order the member was named in the network elicitation interview and as a dichotomous variable of "close, yes/no." Studies that found no association used a Likert scale and others derived a score of closeness from other measurements. We expect that dichotomization of 'closeness' and order named may not be sensitive enough to ascertain the exposure status. Moreoever, we have reason to believe that misclassification may depend on syringe-sharing behaviour. Those who share syringes may be more likely to believe that their network members are close since the act of sharing needles may be so "intimate" that individuals perceive an emotional bond even where one does not exist. This may drive the positive association. However, we cannot rule out the possibility that close relationships with drug-using members may encourage the adoption of risky behaviours.

Three effect estimates found a positive association between multiplexity and sharing syringes (13). However, it is important to note that all three estimates come from the same study, which defined a multiplex social network member as being more than one of the following roles: sex partner, drug-using member, and friend. The authors explain that the need to maintain network relationships and social roles may explain the association between multiplexity and needle sharing (13). More evidence is needed to understand this association.

There was no association between condom use and closeness in two effect estimates (18, 19). Tortu et al. found that the strongest predictor of condom use was being in an HIV serodiscordant relationship (19). Thus, it is possible that tie strength does not play a large role with regards to condom use, especially when the threat of disease is transparent. However, it is difficult to ascertain whether the studies lacked power to detect an association since no confidence limits were reported. Neaigus et al. found that lower perceived social distance to injectors was inversely associated with transitioning to injecting among former injectors (15). The authors explain that even though former injectors may not feel socially "close" to current injectors their presence in the social network means that lines of communication are still open, which provides opportunity for the promotion of drug injecting (15). However, this result represented only a subsample of the study's relatively small sample size, not to mention this was the only study available exploring the relationship between transition to injecting and closeness.

Very few studies distinguished risk-taking social network members from non risk-taking ones. We hypothesized that close relationships with risk-taking social network members would increase risk behaviours, but close relationships with non risk-taking individuals may decrease these actions. Not enough evidence existed to support the latter half of our hypothesis. We feel that through social regulation and tangible assistance, non-risk taking social network members of vulnerable people may play an important role in preventing the spread of infectious diseases. Future studies should explore this possibility.

It is difficult to establish statistical validity with data from hard-to-reach populations such as drug users, the homeless, and sex workers. These groups are highly stigmatised, making the creation of a sampling frame impossible (22). Random sampling is implausible, which precludes analyses that assume no statistical violations. Thus, the effect estimates in all the selected references may present a significant selection bias. Respondent driven sampling, a method of snowball sampling where recruitment is 'tracked', attempts to overcome selection biases presented by other methods and is argued to be the best method for recruiting hard-to-reach populations (22). Despite this, researchers are still in the process of developing and validating statistical methods needed to analyze respondent driven sampling data.

The same difficulty arises when trying to conduct any longitudinal studies. Sex workers, drug users, and the homeless must hide their activities to avoid persecution. This in turn results in unstable housing and environments, which creates difficulties in locating participants for follow-up interviews. Loss- to follow-up is particularly problematic in this target population since many have no means (ex/ phone number) by which they can be reached. Few solutions are available for longitudinal work in this population. Some studies have used outreach to keep participants in the study, however, this method often requires that participants have stable housing and a phone number, and therefore loses information from some of the most marginalised individuals with no such commodities (23, 24).

The selected studies have difficulty ascertaining the reliability of their measures. Although closeness has been found to be reliable and validated in a general population (25), we do not know how reliably it performs with a population that often faces issues regarding addiction and mental illness. In addition, very little research on the reliability of multiplexity and length of relationships within social networks has been conducted. However, Wasserman & Faust note that test-retest measures of reliability for social networks are unlikely to be appropriate, since the ‘true’ values of social network properties remain the same for only the shortest period of time (26). As such, difficulties establishing reliability in social network measures exist at the population level and in the nature of the variables themselves. However, if this is true, it is also true that interventions based on network properties must reflect the variety of changes that occur in an individual’s social sphere. This may prove to be a challenge for future research.

Because many of these studies are cross-sectional, we cannot ascertain the directionality of any of these associations. It is highly plausible that risk behaviours could very well affect the strength of relationships within one’s network. Rothenberg argues that theory-based models and simulations may be the path forward to understanding these transmission dynamics (27). However, empirical estimates needed to build such models are lacking because of the logistical difficulty in obtaining those numbers (27). Thus, he argues that an alliance should be made between empiricists and theoreticians, wherein each side consistently informs the other in order to broaden our understanding of social network dynamics (27). This may be our only path forward given this hard-to-reach population and the difficulties in obtaining social network data.

Limitations of the review

This review is subject to a number of limitations. First of all, we did not include unpublished studies in our review. This could make the study vulnerable to publication bias leading to the ‘file-drawer effect’, wherein null association findings are under-represented in this systematic review. This is exacerbated by the fact that the number of epidemiological social network studies is smaller in number and there is great flexibility in social network definitions and methods (28).

Second, aggregating studies based on an alpha value of 0.05 is not sensitive. One study reported a positive association at the 0.10 level (13), but was classified as having ‘no association’ due to our criteria. Moreover, two studies reported a very strong positive association at the 0.01 level (13, 20), but our results could not capture this. Presenting results proved difficult because of the variation in reporting results among the studies. Three of the studies only provided p values from univariate associations (14, 17, 21). One of the studies did not include effect estimates if the effect was not statistically significant in the multivariate analysis, making it difficult to ascertain if studies either lacked power or there truly was no association (19). Furthermore, each effect estimate was presented as if it were a separate study, giving more weight to studies that presented multiple models. Moreover, we did not apply statistical corrections to studies that looked at more than one outcome, increasing our risk of committing type I error.

This review presents the available evidence on the association between closeness, multiplexity, duration of relationship and drug behaviours, drug equipment sharing, and condom use. Strong evidence is not yet available to make firm conclusions or suggest interventions. However, this review highlights important considerations and issues for future research, including the need to develop analysis strategies for hard-to-reach population data; the need to develop longitudinal sampling strategies for hard-to-reach populations; the need to establish valid social network measures, and more importantly, the need to determine how we can harness the power of dynamic networks to influence behaviour. There has been increasing interest in the use of social networks to elicit change in individuals—it is important that we use available evidence to inform the design of future studies and interventions.

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Challenges and Successes in the Design and Analysis of Respondent Driven Sampling for Hidden Populations: A Review of Current Methodology

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Chapter Two: Challenges and Successes in the Design and Analysis of Respondent Driven Sampling for Hidden Populations: A Review of Current Methodology

One of the objectives of this research was to identify what strategies exist for sampling hard to reach populations and explore their limitations. One of the current ways of gathering data from such populations is a method called respondent driven sampling (RDS), which uses respondents to recruit future participants. Each respondent is given a set number of recruitment coupons to distribute to their contacts; when one of their recruits participates in the study, they too are given a set of coupons. The coupons are tracked and enable researchers to study the pattern of recruitment. There has been ongoing debate on how to best analyze respondent driven sampling data since it comes from a non-probability sample. In turn, many assumptions are violated when performing traditional statistical analyses. This chapter presents a review of the strengths and limitations of current methods of sampling hard to reach populations with a focus on Respondent driven sampling. Moreover, it summarizes the latest statistical techniques suggested to account for the non-random nature of a respondent driven sample. In this chapter, we argue that RDS avoids the severe selection biases presented by other methods, however, methods for correcting for the non-probability sample need to be further developed.

Challenges and Successes in the Design and Analysis of Respondent Driven sampling for Hidden Populations: A Review of Current Methodology

Abstract:

Introduction: In epidemiology, sampling hidden or hard-to-reach populations has been challenging since many of these groups engage in illegal and/or stigmatized behaviour. Respondent driven sampling is a tracked method of sampling that overcomes these barriers by giving the job of recruitment to the participants. Although research on RDS implementation is emerging, few studies have attempted to summarize this literature and guide researchers through the use of this method. This paper attempts to review the current state of RDS in terms of its design and statistical analysis, as well as describe the current challenges and successes of its implementation.

Methods: A literature review was conducted reviewing core articles describing the original design of RDS, actual studies implementing RDS, and lessons learned from the field. We also reviewed the statistical literature describing existing RDS estimators and issues that exist with inferring from RDS data.

Results: In many studies, RDS has been found to be a fast and effective method of recruiting hard-to-reach populations. However, current statistical RDS estimators in use are based on unrealistic assumptions, making it difficult to infer results to the greater population.

Discussion: Despite statistical limitations, RDS continues to be the only method that avoids the severe selection biases that exist when sampling hidden populations using traditional techniques. For this reason, researchers are encouraged to use RDS when dealing with especially marginalized populations. Future research should continue improving statistical techniques for analyzing RDS data.

Article:

Introduction

Vulnerable populations face severe health inequities in developed countries across the world. STIs and bloodborne pathogens are no exception. A recent study done in Toronto, Canada found that an estimated 19% of tuberculosis cases among the homeless resulted in death within 12 months of being diagnosed (1). A study of street youth in Montreal, Canada found that the prevalence of Hepatitis C Virus was higher than the general Canadian population (12.6% vs. 8%) (2). In the United States, an estimated 6600 injection drug users were diagnosed with HIV in 2006 (3). Reasons for these disparities, and potential prevention strategies, must be given attention through research.

The problem with sampling disenfranchised populations such as substance abusers and prostitutes is the fact that they remain largely ‘hidden’ or ‘hard-to-reach.’ This refers to the difficulty with sampling the population due to the lack of a proper sampling frame, which is often in turn due to members' unwillingness to identify themselves because of stigma or fear of persecution. Consequently some studies fail to capture some of the most vulnerable members of these populations.

This article outlines an approach for sampling hidden populations called respondent driven sampling (RDS), in which we will discuss the type of information that can be generated using RDS data, as well as current limitations. This article will also introduce the concept of social networks and the value of social network characteristics in understanding infectious disease transmission among vulnerable populations.

Methods for Sampling Hidden Populations

As outlined by Salganik and Heckathorn, the following three methods take advantage of traditional sampling methods, but fail to take into account the truly 'hidden' nature of these populations (4). First, one may attempt to create a sampling frame of the hidden population, select individuals from this frame, and calculate the sampling probability of these individuals (4). This would be a relatively simple approach; however, frame construction is not only resource-intensive, but is nearly impossible for many hidden populations.

The second approach outlined by Salganik and Heckathorn would be to use random digit dialling to reach a large number of individuals, followed by screening for inclusion into the sample (4). However, this method is not only prohibitively expensive, but members of vulnerable populations such as substance abusers or street youth are unlikely to have phones through which they may be reached, creating a significant selection bias.

A third approach takes advantage of institutions where vulnerable populations congregate. To target street youth, for example, homeless youth shelters may be an excellent place to recruit study members (4). Although sampling from these institutions overcomes the obstacles of requiring phones for participation or making a sampling frame, inference can only be made about those who attend these venues (4).

Targeted sampling, or street outreach, has also been used to collect information from hidden populations (5). This method involves sending field workers to various venues and locations, not necessarily institutions or public areas, to recruit individuals (5). Despite these efforts, this method suffers the same problem as the previous technique: the sample is not random, and it overlooks people at private venues.

Key informant sampling involves drawing "knowledgeable" members from the hidden population, and asking them about behaviours of members, excluding themselves (6). This was designed to avoid response bias with respect to sensitive questions. However, the validity of proxy report is questionable, and again, the sample is not drawn at random.

A more complex approach has been suggested by Muhib et al (7). This technique, called time-space sampling, requires an initial fieldwork step needed to create a sampling frame with information on when members of the hidden population meet, and at which locations (7). This information provides researcher with information to make a primary sampling unit composed of the venue, date, and time. Each primary sampling unit is either chosen at random, sometimes with a sampling frame corresponding to the yield at the location-time (7). When the PSU is chosen, members of the target population are systematically selected for interview. By sampling PSUs with a known probability, statistical inferences can be made about the target population. Major issues with this approach include the inability for researchers to access locations where members of the hidden population can be found, as well as safety issues for the researchers.

Respondent Driven Sampling Method

In 1997, Heckathorn introduced a new method of collecting information about the behaviour of hidden populations called "Respondent Driven Sampling" (RDS) (8). The method was derived from snowball sampling introduced by Coleman (9), where future participants are recruited in a chain-referral manner through the friendship networks of respondents. In RDS, respondents themselves are responsible for recruiting the next wave of participants through referral "coupons," which also work to document the recruitment chain (8).

The process begins when "seeds," or initial participants, are selected by the investigators. Seeds are then interviewed at a location that is ideally easily accessible. Next, seeds are paid and supplied with *c* uniquely coded referral coupons. C should be a quantity big enough so that recruitment does not stop even if some participants do not recruit, but small enough to allow many sampling waves to occur (4). The latter requirement ensures that all members of the hidden population have a non-zero probability of being selected (4). In this "dual incentive" process, participants are paid upon completion of the study, and are also paid whenever one of their recruits is interviewed (4, 8). According to Heckathorn, this is an effective way of encouraging participation due to the combination of internal motivation and peer group influence (8). A new wave of recruitment starts when a recruit presents to the researcher with one of the referral coupons. The coupon number is documented, and the interview is then conducted. The recruitment chain continues until the desired sample size is reached.

Design Challenges and Successes of Respondent Driven Sampling

In practice, the RDS design has many advantages compared to other sampling techniques, but also many challenges. Head-to-head studies comparing RDS to other techniques, namely, targeted sampling and time space sampling, have been conducted to investigate the claims of the RDS authors. In a study among injection drug users (IDUs) in three US cities, RDS resulted in a higher proportion of eligible participants among those screened, as well as less staff time per recruit (10). Cost-efficiency was comparable between the two techniques (10). Among IDUs in the Russian Federation and Eastern Europe, RDS was found to be slightly faster than targeted sampling, but also slightly more resource intensive (11). It was also questionable whether RDS captured more “marginalized” populations than targeted sampling (11). Thus, RDS has been found to be a faster method than targeted sampling, but whether RDS is less costly and able to reach all marginalized populations is open to discussion. Clark et al. compared RDS with other sampling methods for cancer screening among unmarried middle-aged and older men who partner with men and women who partner with women (12). They found that RDS was less superior to print media with respect to cost and participant enrolment, but more superior in these measures when compared to targeted sampling at health fairs and community events (12).

Comparisons of time-space sampling and RDS have also been done. A study regarding female sex workers in two Vietnamese cities found that RDS was able to reach populations that would not theoretically be reached by time space sampling, such as those that recruit clients via pimp, telephone, or internet (13). In a study of men who have sex with men in Guatemala City, RDS had a higher population size estimate than that obtained by time space sampling (14). The authors assert that this can be attributed to the ability of RDS to access non venue-attending participants (14). Compared to time space sampling, RDS was better able to recruit lower socioeconomic status participants among men who have sex with men in Fortaleza, Brazil (15). These studies suggest that RDS is superior to time-space sampling with regards to capturing less accessible individuals.

Several studies have outlined experiences and lessons learned while implementing RDS in the field. Studies of IDU in Mexican-American border cities (16), men who have sex with men and female sex workers in Papua New Guinea (17), and household heads in an open cohort in rural Uganda (18), have shown that RDS is indeed a fast method of recruitment across a variety of countries and settings. However, a study of sex workers in Eastern Europe found that RDS recruitment was slow due to weak social networks and the hidden nature of the sex trade (19). Similarly, a study conducted in Estonia found recruitment of female sex workers to be slower compared to IDUs due to smaller personal networks and weak interaction with other FSWs (20). Thus, the interconnectedness and type of hidden population may affect the speed of recruitment.

Early statistical theory about RDS asserts that estimates do not depend on initial seed selection (for more information see (4, 21)). Despite this, studies in Canada have carefully chosen seeds to ensure the target population was well represented. In the studies we have conducted, seeds were selected to reflect the diversity of the target population. In both the Winnipeg and the Ottawa Vulnerable Peoples' Studies, our target populations were vulnerable groups for STIs and bloodborne pathogens, namely, underhoused people, sex workers, people who use drugs, and street youth. Thus, seeds were selected from each of these groups. Leonard et al. had a more homogeneous group with respect to risk behavior, and so seeds were selected based on other factors such as location (one seed from the east end of the city, one from the west); language ability (at least one French and one English-speaking IDU); and race (minority/ non-minority) (22). As the statistical RDS literature continues to grow, seed selection remains a topic of discussion and debate. Table 1 summarizes RDS studies that have been performed in a Canadian setting (23-25).

Some challenges with the design of RDS have involved the dual incentive system proposed by Heckathorn (8). Some have argued that by paying the recruiter, the participant's confidentiality is breached (26). Moreover, according to a study by Scott (27), some recruiters have physically or verbally abused the recipients of their coupons to force participation and obtain money from the recruitment process. This brought to light the idea of coercion in the recruitment process. Rather than employ the dual incentive process, Wylie et al. used participant-only compensation and found that RDS could be successfully deployed without recruiter compensation (28). Leonard et al. also provided participation-only compensation and nevertheless found that interest outweighed the study capacity (22). We hypothesize that in some cases secondary incentives may be unnecessary since recruiters may be informally paid "in-kind." These informal payments, for example, helping one move or sharing goods (e.g. meals), may be sufficient to drive recruitment. Further attention must be given to the use of coupons as a means of currency and coercion, as well as these implications in the ethics and integrity of RDS and resulting data.

Table 1 Summary of Canadian Studies using RDS

Study Title/ Authors	Target sample size	Actual sample size	Population Type	City	Secondary incentives?	Number of coupons	# waves	Range of component size
Sobota and Tranter, 2010	Not mentioned	295	Injection drug users, substance users	Thunder Bay	Yes. $5.00 per recruit	3	6	1-134
Leonard et al, 2011	~400	406	Injection drug users	Ottawa, ON	Yes	3	22	1-253
Wylie, Jolly et al., 2010	600	600	Most at-risk populations (IDUs, sex work-and street-involved individuals)	Winnipeg, MB	No	3	9	1-46
Bauer et al, 2010 TransPULSE	No specific target set	307	Trans communities 16+	Ontario	Only toward the end of recruitment	3	10	unknown
Hathaway, 2010 The four-city study	160* (Not enough for stat. analysis)	160	Marijuana users	Toronto, Montreal, Halifax, Vancouver	Yes. Offered an entry for each referral in a draw (gift certificate worth $500)	3 (permitted word-of-mouth referral after several months of slow recruitment)	unknown	unknown
Jolly et al. The Ottawa Vulnerable Peoples' Study	226	226	Most at-risk populations for STBBIs	Ottawa, Ontario	No	3	22	1-132

Inference in Respondent Driven sampling

Before inference can be made to the hidden population, it is important to point out obvious statistical concerns surrounding the RDS sampling design. First, RDS is not even close to being a simple random sample (29) and so the assumptions of independent observations are violated and traditional inference methods cannot be used. Secondly, seeds are not drawn randomly and so there is not an equal chance of each individual being selected, meaning that future recruits can be heavily dependent on initial recruit selection (8). Third, individuals who know more people are more likely to be recruited; in other words, people with a high “degree” are more likely to be selected (4). These problems have frustrated researchers and hampered efforts to make RDS a mainstream method of collecting and analyzing data.

With the exception of the naïve and Successive Sampling estimators, all estimators below treat the sample as a random walk on the social network. A random walk is a type of Markov Chain where a variable can either move forward into one state, or remain stationary: in the case of RDS, a participant can either choose to recruit or not recruit at all. The assumptions of modeling RDS as a Markov Chain random walk process are described in detail elsewhere (30, 31) but some major assumptions will be discussed below. Moreover, Gile and Tomas (32) provide more detailed descriptions of the estimators below; the purpose here will be to simply introduce them (33).

The Naive Estimator

The naïve estimator uses the sample proportion to estimate the population proportion (8, 33). The naïve estimator assumes that respondents are sampled randomly from the population, even though this is not true in RDS. Regardless, the naïve estimator has been used in the literature when estimators that adjust for RDS do not produce significantly different results (see (34, 35)). Generalized estimating equations have also been considered for RDS data. In RDS, data are non-independent because of recruitment patterns: network members tend to recruit those who are like themselves, a phenomenon called *homophily* (36). Thus, an individual chain of recruitment forms a set of connected nodes, called a component, which comprises individuals who are similar to one another. These components may be considered to be clusters in generalized estimating equations.

The Salganik-Heckathorn Estimator

The estimator proposed by Salganik and Heckathorn has theoretical foundations in social network theory and Markov chain theory (4). The estimator uses transition probabilities, which are determined by calculating the proportion of recruitments from one group to another. These recruitment probabilities are adjusted by the "degree", the self-reported number of people in one's network. The result is an equation that estimates the proportion of the population in each group. To accompany this estimator of population proportions, Salganik also devised a bootstrap approach to determine variance estimates (37).

The Heckathorn Estimator

The Heckathorn estimator also relies on Markov chain theory and social network theory, and can be considered an extension of the Salganik-Heckathorn estimator (33, 36). The Heckathorn estimator, however, adjusts the degree term in order to account for recruitment effectiveness and differential recruitment (36). The result is an equation that not only takes recruitment patterns into consideration, but can be used to provide estimates for continuous variables. The current RDS analysis tool, RDSAT, employs the Heckathorn estimator.

The Volz-Heckathorn Estimator

The estimator presented by Volz and Heckathorn relies on Markov Chain sampling theory and the theory of sampling with unequal probabilities (30). The authors use inclusion probabilities, which are found by treating the sample as a random walk on the network (30). The resulting Volz-Heckathorn estimator can be used for both continuous and categorical variables. Volz and Heckathorn also provide a variance estimator based on algebraic approximations to a non-branching recruitment chain (38).

Successive Sampling Estimator

The Successive Sampling estimator also relies on the theory of sampling with unequal probabilities, but rather than using Markov Chain theory, it relies on successive sampling, or probability proportional to size (32). Successive sampling is a sampling scheme where respondents in future samples are selected in a way that some respondents are similar to ones from past sample respondents (32). More studies are needed to evaluate this estimator on real networks.

Analysis Limitations of Respondent Driven sampling

Despite the fact that several estimators are available for RDS analysis, the strict assumptions necessary for their use are often unrealistic. Research is only starting to emerge assessing current methodology and the extent to which the estimators are biased if the assumptions are violated. Here, we present a brief summary of the limitations of these estimators with a focus on bottlenecks and their role in causing bias in estimation.

Several studies have asserted that there are a variety of assumptions and oversimplifications that make Markov Chain techniques inappropriate for analyzing RDS data (38, 39), which affect all of the Salganik-Heckathorn, Heckathorn, and Volz-Heckathorn estimators. First, these estimators are derived from a model of a non-branching, with-replacement random walk process at equilibrium. However, because more than one coupon is distributed to each respondent to ensure the continuation of recruitment, the process resembles a referral "tree" rather than a chain (39). Second, the random walk process assumes that the population is infinite, even though hidden populations have finite membership (38). Third, the random walk process assumes that data are complete, even though non-response is often an issue in RDS studies (38). Finally, Neely points out that the random walk process assumes with-replacement sampling, although RDS studies strongly avoid having individuals repeat surveys (38). The estimators are based on even more assumptions that we are sampling from a random walk on a network, and that the distribution of the process is stationary. However, using simulated networks, Gile and Handcock came to the conclusion that the stationary process is highly sensitive to many of these assumptions, and whether the process can actually be considered stationary is up for discussion (31). Poon et al. also assert that recruitment processes are influenced by the attributes of recruiters at every wave: not only are the attributes of a respondent influenced by their recruiter, but by their recruiter's recruiter, and so forth (39). This is not a characteristic of Markov Chains, which are said to be memoryless. Although the Successive Sampling estimator takes these processes into account, more studies need to be conducted that assess this methodology using not only simulated, but real networks.

Finally, the recruitment process is influenced by a variety of immeasurable characteristics which can influence the direction of the recruitment tree. This brings up the concept of "bottlenecks." Bottlenecks refer to the propensity for sampling to occur only in one part of the entire social network based on some quantity z (40). For example, suppose one would like to estimate the prevalence of HIV in a group of injection drug users. A highly homophilic population would mean that HIV positive participants are more likely to have HIV positive recruits; this would lead to a bottleneck structure in which the majority of participants would be infected, leading to an overestimate of the HIV prevalence. Goel and Salganik also show that even when there are many ties between infected and non-infected individuals, bottlenecks that exist in other parts of the network structure can result in large variance (40). Thus even though one could possibly detect and adjust for the bias caused by one bottleneck, there may be others in the network structure that are not easily identified and corrected.

Finally, although the naïve estimator has been criticized for unrealistic assumptions about normality, studies using real networks have found that RDSAT-adjusted point and variance estimates do not differ significantly from those using traditional statistical techniques. Strathdee et al. found that odds ratios and

95% confidence intervals generated by RDSAT were not significantly different from their unadjusted, logistic model looking at HIV infection among IDUs in Tijuana, Mexico (34). Pollini et al. found that RDSAT adjusted odds ratios did not differ from non-adjusted odds ratios by more than 9%, and all p values remained significant in models looking at arrests among IDUs in Tijuana and Cuidad, Mexico (35). Li et al. also found that there were no substantial differences between RDS weighted multivariate analyses and unweighted analyses in their study on young drug users in China (41). McCreesh et al. found that RDS statistical techniques were unable to correct biases associated with the oversampling of younger, higher socioeconomic status males in their study of household heads in Uganda (18). These findings suggest that RDS statistical techniques may offer relatively little real advantage over the naïve estimator. We recommend that future studies continue to use the naïve estimate and explicitly state the limitations and potential biases posed by RDS.

The Future of RDS

Currently, RDS is the only method that can avoid the selection biases associated with, random digit dialing, targeted sampling and time space sampling. The severity of these selection biases cannot be ignored.

The fact remains that participants are the best recruiters of their own population since they recruit through their social networks. In fact, extensive research has been done on the small world problem, which states that every person in the world can be reached to another person via six steps (42). In turn, these social networks span large geographic areas, include individuals who do not attend public institutions, and comprise those who are often stigmatized by the general population. Abdul-Quader et al. demonstrated that, despite the recruitment of seeds from only the Lower East Side of New York City, respondents were drawn from a total of 70 zip codes, with the furthest being more than 200 miles away (43). We have also demonstrated the ability of sexual networks to span large geographic areas, with some individuals having the propensity to engage in very long distance relationships (44). Upon comparing time-location sampling and snowball sampling in men who have sex with men in Brazil, Kendall et al. found that RDS was more effective at reaching low-socioeconomic status men who have sex with men, an even less accessible subpopulation due to lack of resources to attend venues where recruitment for the other sampling strategies occurred (15). Moreover, RDS has been found to be effective among injection drug users in Albania, who often avoid open contact with the rest of society (45). The breadth of coverage, which avoids grave selection biases posed by other methods, along with its applicability across different settings provides strong reasoning for the continued use of RDS.

Moreover, statistical limitations in RDS do not mean a lack of information. Rather, results that are obtained from RDS provide insight on social networks, powerful social structures that govern transactions between individuals, from financial exchange and business, to friendship and kinship. A natural extension is the application of these social structures to infectious diseases, where the transmission of disease is dependent on contact between individuals. Research has already shown that disease transmission follows the pattern of social networks. (28, 46-48). Moreover, research has also shown that risk behaviors for infectious diseases are associated with social network structure and composition. De et al. provide a comprehensive systematic review outlining network size, density, position, and composition in relation to the sharing of drug equipment (49). Wejnert provides an overview of how "recruitments" in RDS can be used to study social network characteristics such as homophily, affiliation, and network size, since recruitments are chosen at random from the social network (50).

Recently, Tomas and Gile provided guidelines for use of current estimators under particular sampling conditions (33). Recent studies look beyond Markov chain theory, proposing stochastic context-free grammars to model the RDS recruitment process. This development allows the interpretation of RDS as a branching process rather than a chain-like structure (39). Stochastic context-free grammars may have the potential to perform hypothesis testing on RDS data, even accounting for the dynamics of the recruitment process due to latent variables (39). The use of RDS for making estimates about hidden populations continues to be an area of discussion and growth in the literature.

The possibilities for inference in RDS continue to be explored. If RDS is the only method that can provide breadth of coverage, avoid severe selection biases, and provide disease transmission information about hidden populations, then in spite of statistical limitations, RDS should indeed be used to study these populations. The goal for future studies will be to improve statistical techniques that allow one to make inferences about a hidden population from an RDS sample. For now, social networks are able to provide crucial health information necessitated by the needs of hidden populations.

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Supportive Strong Ties and their Association with Drug Use

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Chapter Three: Supportive Strong Ties and their Association with Drug Use

This chapter consists of the third and final manuscript of this research investigating tie strength measures and risk behaviours. It consists of a primary analysis of data collected from unstably housed individuals, sex workers, and people who use drugs in Ottawa, Canada. Two outcomes were investigated: crack use in the last 6 months and injection drug use in the last 6 months. The exposure variables were closeness, relationship duration, and multiplexity. Logistic regression models were used to explore these relationships. This research contributes new insights on how having strong-tie support network members can promote health-protective behaviours.

Supportive Strong Ties and their Association with Drug Use

Abstract:

Introduction: The social networks of people who use illicit drugs are a source of untapped potential for drug cessation. In separate studies, social support, relationship quality, and peer risk-taking behaviours have all been shown to impact health. However, we do not know the association between drug use and having a social network member who embodies all of these characteristics. We sought to find the association between crack smoking and intravenous drug use in the last 6 months and the presence of a supportive network member who fit the profile of a "strong tie," which was characterized as either being considered 'close,' long-term, or having multiple roles.

Methods: Using respondent driven sampling, social network data were collected from underhoused people, sex workers, people who use drugs, and street youth (n=225) from Ottawa, Canada in 2010. Network members were characterized as 'risk-taking' or 'non-risk taking' depending on whether they used drugs and whether they were a sex partner with whom condoms were not used. Multivariate logistic regression was used to assess the association between supportive strong ties that were either risk-taking or non-risk taking and crack smoking and intravenous drug use in the last 6 months.

Results: 31.1% of participants were female, 83.6% were Caucasian, 54.7% had less than high school education, 46.7% had injected drugs in the last 6 months, and 75.0% had smoked crack in the last 6 months. The mean age was 41.4 years (SD=10.6). Having a supportive network member who was considered "close" and did not engage in risk-taking was inversely associated with smoking crack in the last 6 months (aOR=0.69, 95% CI: 0.56-0.85). Supportive "close" non-risk taking members were also protective against injecting in the last 6 months, but only for heterosexuals (heterosexuals: aOR=0.24, 95% CI: 0.16-0.37; non-heterosexuals: aOR=2.50, 95% CI: 1.07-5.78).

Conclusion: "Close" supportive network members who are not risky sex partners and who do not engage in drugs may represent a valuable point of intervention for drug cessation programs.

Article:

Introduction

People who inject drugs or smoke crack face daily threats to their mental and physical well-being. Epidemiological studies have shown that drug use and addiction are associated with a lower quality of life (1-4) poorer mental health (5, 6), and higher mortality rates (7, 8). Smoking crack and injecting drugs also give rise to behaviours responsible for HIV (9, 10), Hepatitis C (11, 12), and other bloodborne illnesses (13). To compound these problems, people who use drugs often face poverty, social exclusion and stigma (14). It is important to determine the factors that encourage and discourage the use of drugs to create appropriate interventions for drug prevention and cessation.

Almost all current population health frameworks include the social environment as an important determinant of health (15). Over the years, researchers have used several concepts to define the social environment, such as social networks, which are a set of individuals and the relationships between them (16) and social support, which is the perception that one is cared for and has assistance (17). Berkman's framework explains that social networks provide opportunities for psychosocial mechanisms such as social support and social influence, which then impact health through behavioral, psychological, and physiologic pathways (18). The framework recognizes these concepts are related in a dynamic way, creating an environment that can promote or denigrate health.

Thus, we attempt to capture one process within this dynamic model. In particular, we wish to look at the social network characteristic of 'tie strength,' which can give rise to social support, which in turn may affect drug behaviours. Network members who have a "strong" relationship with a drug user and are able to provide instrumental support may have the ability to change the course of their peer's drug patterns (19).

Tie strength, or relationship strength, is characterized by several factors, including closeness or emotional intensity, duration, and multiplexity (20). Multiplexity is the characteristic of having more than one role, such as baby sitter, drug dealer and neighbor (21, 22). People who play multiple roles in an individual's life are said to have a 'strong tie' with that individual. A number of studies have linked closeness (23), relationship duration (24), and multiplexity (25-27) to patterns of delinquent behaviour and drug use.

Relationships considered "strong" are important in communities of lower socioeconomic status, where food, child care and housing are shared with others to cope with scarcity (28). Thus, as the framework by Berkman demonstrates, strong ties can give rise to instrumental support or tangible assistance, which is the provision of material goods, financial assistance, or services (18). This type of social support can be particularly valuable among people who use drugs, many of whom face financial limitations and require aid for basic needs.

However, we have reason to believe these strong-tie support relationships differentially impact health depending on whether risk behaviors are involved. Research has shown that people with a high proportion of drug-using members in their network are more likely to engage in drugs themselves (29, 30). Moreover, there is evidence that people who use drugs are less likely to cease risky drug behaviours when they have drug-using network members who provide support (31). Furthermore, we also have reason to believe that the underlying psychological mechanisms which give rise to risky sex (sex where condoms are not used) may contribute to drug use as well (32). Thus, the presence of risk-taking relationships which we will call negative relationships, may impact drug use in different ways than non-risk taking (i.e., positive) ones.

Although there has been evidence of the impacts of having support, strong-tie, positive and negative relationships separately in one's network, we do not know the effect of having relationships that embody all of these characteristics on drug use. Drug associated morbidity and mortality cost an estimated $177.4 billion in the United States in 2000 (33). Moreover, many interventions aimed at addictions rely on professionals and institutions, creating a costly and often unsustainable solution. Existing members of drug users' networks who exert positive influences on one's life are a source of untapped potential for intervention. We believe these individuals provide both the peer influences and social resources necessary for drug cessation.

We hypothesize that the existence of non-risk taking support network members who are either 1) close 2) long-term or 3) multiplex will be associated with two outcomes: crack smoking in the last 6 months and injection drug use in the last 6 months. In other words, marginalized individuals with at least one positive network member who exhibits a strong-tie quality will have a lowered odds of recent crack smoking and recent injection drug use.

Using respondent driven sampling, we interviewed 226 street-involved and/or drug-using individuals from the Ottawa, ON area using an instrument that included a social network inventory. We defined 'negative' network members as either risky (non condom-using) sex partners or drug-using members. 'Positive' network members were defined as condom-using partners or non-drug using members. We sought the presence of a strong-tie positive network member and we applied multivariate logistic regression to see if this presence was related to smoking crack or injecting drugs. We found that the presence of a "close" network member who does not engage in drugs or is a risky sex partner was inversely associated with injecting in the last 6 months for heterosexuals. However, the presence of this type of network member actually increased the odds of injecting among non-heterosexuals. We also found that the presence of a close network member decreased the odds of smoking crack within the last 6 months, regardless of sexuality.

Methods

Recruitment

Participants were recruited into a cross-sectional study using respondent-driven sampling (34, 35) in the Ottawa, Canada area between June 2010 and November 2010. Respondent-driven sampling was used because marginalized people represent a 'hidden' population, meaning a random or representative sample of this population is difficult to attain (36). In this type of sampling technique, existing study subjects are used to recruit future study subjects through chain referral (34, 35, 37). This technique has been employed in previous research to study marginalized populations (38-42). Seeds were selected based on the study target sub-populations (underhoused people, sex workers, people who use drugs, and street youth) and were given three uniquely coded coupons to distribute to their network members for recruitment into the study. Recruitment waves continued as participants returning with coupons were also given coupons to distribute to their network members. Interviews were done face-to-face by experienced nurse interviewers in a variety of private settings, including community health centres and participants' homes.

Study Instrument

The study used a structured survey instrument which was piloted successfully in Winnipeg in 2004 (43). The instrument comprised two sections. In the first section, participants answered questions regarding demographics and other individual-level information about perceived health as well as drug, alcohol, and solvent use. The second section comprised the network elicitation component. Participants were asked to enumerate up to 10 people with whom they had more than casual contact over the last three months. Subjects were asked to use initials and anonymous identifiers to name their contacts in order to reduce participant burden and to maintain confidentiality.

Network members who provided support were defined as a positive answer to either "Could you depend on [person] to do you a small favour (e.g. babysitting, helping you to a doctor's appointment)?" or "Could you depend on [person] for a big favour (e.g. you needed a place to stay for the night or you needed a loan of a fairly large amount of money- >$100?)." This question has been applied in other social network studies (44) .

Network members who engaged in drugs or risky behavior were defined as "negative support network members" and were identified by: a "yes" response to any of the following questions: "Have you ever smoked cracked with/ used any other types of drugs with [person]?" or "Do you regularly (approximately once a week or more) drink alcohol with [person]?"; a nomination to "To your knowledge, which of these people have injected drugs in the past 6 months?" or "Thinking back to the list of people in your social network, which of them have you had sex with?"/ "In the past 6 months, how frequently have you used condoms with [person]?"

Multiplex was defined as having 2 or more roles. Roles considered were drug, sex, kinship and neighbour roles. We asked participants "What is the relationship of [person] to you?" 'Kin' was defined as a positive answer to 'Family (by birth or adoption),' 'Spouse/ boy/girlfriend' or 'Friend'. We also asked "How physically close does each person live in comparison to where you live?" 'Neighbour' was defined as having a positive answer to living in the same residence, apartment block, housing complex, or neighbourhood. Drug roles were considered as a positive response to the following questions: "Have you ever smoked cracked with/ used any other types of drugs with [person]?" or "Do you regularly (approximately once a week or more) drink alcohol with [person]?" Sex role was defined as a positive response to "Thinking back to the list of people in your social network, which of them have you had sex with?"

"Close" was defined as a positive response to either 'Close' or 'Very close' to the question "How close are you to each of the people on the list?" A long-term network member was defined as having known the person for more than one year. We asked "How long have you known [person]" Time categories were "Less than 6 months; 6 months to 1 year, 1 year to 5 years, and greater than 5 years." The 1 year time point within relationships appears to be a significant predictor in behavioral change. For example, among people who use drugs, needle sharing has been associated with injecting together for more than 1 year (45). Knowing a person for less than 1 year is also an indicator of greater network turnover (45), which may make networks more difficult to intervene. We dichotomized length of time known as being "Greater than 1 year" or "Less than 1 year".

For each participant, we summed the number of support network members they considered long-term, close, or multiplex within each of the 'positive' and 'negative' categories. We then divided this number by the total number of social network members they had nominated to create a proportion. Proportions are used for 'content variables,' which describes the quality of the ties within the network (46). Because proportions were not normally distributed, we created categorical levels within each tie strength variable based on the distribution of proportions. Non-normal distributions are common in social network data (47). We thus had 6 exposure variables of interest: 1) presence of at least one close positive support network member (yes/no) 2) presence of at least one multiplex positive support network member (yes/no) 3) presence of at least one long-term positive support network member (yes/no) 4) (high/medium/low) levels of close negative support network members 5) presence of at least one multiplex negative support network member and 6) (high/medium/low) levels of long-term negative support network members.

Demographic variables used as control variables were age, sex, race, source of income, high school education and sexual orientation. Other studies have demonstrated the importance of these variables with respect to network processes and risk behaviors (45). Age was coded continuously; sex was coded 'male' or 'female'; race was coded as 'Caucasian' or 'other'; source of income was coded as 'regular work' or 'non-regular work' (panhandling, hustling, government assistance, etc.) and sexual orientation was coded as 'heterosexual' or 'lesbian, gay, bisexual, transsexual, or questioning.' We also asked if the participant considered themselves a 'hobo' or 'traveller;' this variable was coded as 'yes' or 'no.' Incarceration within the last 6 month, a self report of anxiety or depression, and a diagnosis of a mental health condition by a professional were also treated as dichotomous variables.

We also included sexual history variables, such as number of partners in the last 6 months, sex work in the last 6 months, and purchasing sex within the last 6 months. Drug use within the last 6 months was also considered. High popularity and collinearity among non-injected morphine, heroin, Oxycontin, opium and Dilaudid allowed these variables to be grouped into the variable 'popular non-injection drug use (yes/no).'

Statistical Analyses

The main purpose of the data analysis was to see if strong-tie support networks were associated with recent injection drug use and crack use. All statistical analyses were performed using SAS 9.3 (SAS Institute Inc., Cary, North Carolina). X^2 or Fisher's exact test was used to evaluate the univariate association between each categorical variable and risk behaviors within the sub-populations of those who had ever injected, ever smoked crack, and had sex within the last 6 months. The Cochran-Armitage test for trend was used for social network score variables that had more than two levels. Univariate associations with age were tested using Wilcoxon rank sums and t-tests.

Multivariate logistic regression models identified if independent associations existed between tie strength in support networks and recent crack smoking or injecting. All variables that had obtained a significance level of <25% in the univariate analysis were considered for the multivariate models. A manual procedure was used to select variables for inclusion into the model, wherein unadjusted odds ratios for each relationship quality variable were compared to adjusted values. A percent change of greater than 10% in the estimate indicated potential confounders. Likelihood ratio tests were used to compare nested models with a significance level of 5.0%. Statistical effect modifiers were tested using likelihood ratio tests with a significance level of 5.0%. All 2-way interactions with relationship quality variables were explored. Hosmer-Lemeshow goodness-of-fit statistics were used to provide crude evidence of 'good fit.' C statistics and ROC plots were generated to examine how effectively each model described the outcomes of interest.

Multistage multiple imputation was used to account for missingness in the data. To explore the potential effects of RDS on our estimates, we compared the above models with models using Generalised Estimating Equations (GEE). GEE models may take into account potential clustering due to the recruitment trees. Previous work has shown that connected social networks tend to be more homogeneous with respect to risk behaviours and disease status (48, 49), thus recruitment trees may be considered clusters.

Results

Table 1. The distribution of demographic and mental health characteristics with respect to drug behaviours in a marginalized population in Ottawa, ON

	Whole population (n=225)	Ever Injected (n=164)			Ever smoked crack (n=204)		
		Did not inject in the last 6 months (n=59)	Injected in the Last 6 months (n=105)	P Value	Did not smoke crack in the last 6 months (n=36)	Smoked Crack in the last 6 months (n=168)	P value
	n (%)	n (%)	n (%)		n (%)	n (%)	
High School or higher	102 (45.3)	28 (44.4)	38 (57.6)	0.16	14 (16.1)	73 (82.9)	0.62
Less than high school	123 (54.7)	31 (31.6)	67 (68.4)		22 (18.8)	95 (81.2)	
Regular work	14 (6.2)	3 (33.3)	6 (66.7)	0.87	1 (8.3)	11 (91.7)	0.38
Non-regular work	211 (93.8)	56 (36.1)	99 (63.9)		35 (18.2)	157 (81.8)	
Independent housing	107 (47.6)	29 (35.4)	53 (64.6)	0.87	20 (20.8)	76 (79.2)	0.26
Non-independent housing	118 (52.4)	30 (36.6)	52 (64.4)		16 (14.8)	92 (85.2)	
Caucasian	188 (83.6)	49 (36.0)	87 (64.0)	0.97	30 (17.9)	138 (82.1)	0.87
Other	37 (16.4)	10 (35.7)	18 (64.3)		6 (16.7)	30 (83.3)	
Male	155 (68.9)	46 (42.6)	62 (57.4)	0.01	29 (21.2)	108 (78.8)	0.06
Female	70 (31.1)	13 (23.2)	43 (76.8)		7 (10.5)	60 (89.6)	
Heterosexual	180 (80)	50 (37.3)	84 (62.7)	0.45	27 (16.2)	140 (83.8)	0.24
Lesbian, Bisexual, Gay, Transsexual, Questioning	45 (20)	9 (30.0)	21 (70.0)		9 (24.3)	28 (75.7)	
Mean age (SD)	41.4 (10.6)	44.6 (8.1)	39.6 (11.7)	0.03	38.6 (12.1)	41.9 (9.9)	0.19
Traveler/ Hobo							
Yes	16 (7.1)	1 (10.0)	9 (90.0)	0.06	1 (6.7)	14 (93.3)	0.57
No	208 (92.4)	57 (37.3)	96 (62.8)		35 (18.6)	153 (81.4)	
Unknown	1 (0.4)	1 (100.0)	0 (0.0)		0 (0.0)	1 (100.0)	
Incarcerated in the last 6 months							
Yes	14 (6.2)	5 (38.5)	8 (61.5)	0.85	2 (14.3)	12 (85.7)	1.0
No	211 (93.4)	54 (35.8)	97 (64.2)		34 (17.9)	156 (82.1)	
Self-reported depression or anxiety in the last 6 months							
Yes	105 (46.7)	24 (29.3)	58 (70.7)	0.07	10 (10.3)	87 (89.7)	0.02
No	119 (52.9)	34 (42.0)	47 (58.0)		26 (24.5)	80 (75.5)	
Unknown	1 (0.4)	1 (100.0)	0 (0.0)		0 (0.0)	1 (100.0)	
Mental health diagnosis							
Yes	145 (64.4)	34 (29.8)	80 (70.2)	0.02	21 (33.3)	116 (66.7)	<0.01
No	76 (33.8)	23 (48.9)	24 (51.1)		14 (21.9)	50 (78.1)	
Unknown	4 (1.8)	2 (66.7)	1 (33.3)		1 (15.3)	2 (84.7)	

Table 2. Distribution of risk-taking behaviours according to type of drug use

	Whole population (n=225)	Ever Injected (n=164)			Ever smoked crack (n=204)		
		Did not inject in the last 6 months (n=59)	Injected in the Last 6 months (n=105)	P Value[a]	Did not smoke crack in the last 6 months (n=36)	Smoked Crack in the last 6 months (n=168)	P value[a]
	n(%)	n (%)	n (%)		n (%)	n (%)	
Total number of sex partners							
≤20	206 (91.6)	54 (36.7)	93 (63.3)	0.38	35 (18.7)	152 (81.3)	0.31
>20	7 (3.1)	3 (50.0)	3 (50.0)		1 (16.7)	5 (83.3)	
≥50	12 (5.3)	2 (18.2)	9 (81.8)		0 (0.0)	11 (100.0)	
Sex work							
Yes	6 (2.7)	3 (60.0)	2 (40.0)	0.35	0 (0.0)	6 (100.0)	0.59
No	219 (97.3)	56 (35.2)	103 (64.8)		36 (18.2)	162 (81.8)	
Purchased sex							
Yes	5 (2.2)	0 (0.0)	3 (100.0)	0.55	0 (0.0)	5 (100.0)	0.59
No	220 (97.8)	59 (36.7)	102 (63.4)		36 (18.1)	163 (81.9)	
Smoked crack in the last 6 months							
Yes	168 (75.0)	43 (31.9)	92 (68.1)	0.02	0 (0.0)	168 (100.0)	N/A
No	56 (25.0)	16 (55.2)	13 (44.8)		36 (100.0)	0 (0.0)	
Cocaine, morphine, heroin, Dilaudid or Oxycontin use in the last 6 months							
Yes	135 (60.0)	29 (24.8)	88 (75.2)	<0.01	10 (7.5)	123 (92.5)	<0.01
No	90 (40.0)	30 (63.8)	17 (36.2)		26 (36.6)	45 (63.4)	
Cannabis use in the last 6 months							
Yes	173 (76.9)	47 (37.0)	80 (62.3)	0.70	31 (19.4)	129 (80.6)	0.22
No	52 (23.1)	12 (62.4)	25 (67.6)		5 (11.4)	39 (88.6)	
Heavy frequent alcohol use in the last 6 months							
Yes	73 (32.4)	26 (50.0)	26 (50.0)	0.01	13 (20.0)	52 (80.0)	0.55
No	151 (67.1)	33 (29.5)	79 (70.5)		23 (16.5)	116 (83.5)	
Unknown	1 (0.44)	0 (0.0)	0 (0.0)		0 (0.0)	0 (0.0)	
Solvent use in the last 6 months							
Yes	1 (0.4)	0 (0.0)	1 (100.0)	1.0	0 (0.0)	1 (100.0)	1.0
No	224 (99.6)	59 (36.2)	104 (63.8)		36 (17.7)	167 (82.3)	
Any injection drug use in the last 6 months							
Yes	105 (46.7)	0 (0.0)	105 (100.0)	N/A	11 (10.7)	92 (89.3)	0.01
No	120 (53.3)	59 (100.0)	0 (0.0)		25 (25.0)	76 (75.0)	

Table 3. Distribution of strong-tie supportive network characteristics according to drug use

	Whole population n=225	Ever Injected (n=164)			Ever smoked crack (n=204)		
		Did not inject in the last 6 months (n=59)	Injected in the Last 6 months (n=105)	P Value	Did not smoke crack in the last 6 months (n=36)	Smoked Crack in the last 6 months (n=168)	P Value
		n (%)	n (%)		n (%)	n (%)	
Negative Support							
Close							
Low	81 (36.0)	18 (32.7)	37 (67.3)	0.52	9 (12.2)	65 (87.8)	0.51
Medium	75 (33.3)	19 (36.5)	33 (63.5)		17 (25.4)	50 (74.6)	
High	69 (30.7)	22 (38.6)	35 (61.4)		10 (15.9)	53 (84.1)	
Multiplex							
Yes	45 (20.0)	13 (37.1)	22 (62.9)	0.09	11 (15.2)	29 (84.8)	0.07
No	180 (80.0)	46 (35.7)	83 (64.3)		25 (27.5)	139 (72.5)	
Long-Term							
Low	85 (37.8)	15 (26.8)	41 (73.2)	0.42	9 (12.0)	66 (88.0)	0.98
Medium	74 (32.9)	26 (47.3)	29 (52.7)		20 (30.3)	46 (69.7)	
High	66 (29.3)	18 (34.0)	35 (66.0)		7 (11.1)	56 (88.9)	
Positive Support							
Close							
Yes	89 (39.6)	27 (48.2)	29 (51.8)	0.02	21 (28.8)	52 (71.2)	<0.01
No	136 (60.4)	32 (30.0)	76 (70.0)		15 (11.5)	116 (88.6)	
Multiplex							
Yes	92 (40.9)	29 (50.9)	28 (49.1)	<0.01	20 (27.0)	54 (73.0)	<0.01
No	133 (59.1)	30 (28.0)	77 (72.0)		16 (12.3)	114 (87.7)	
Long-Term							
Yes	99 (44.0)	29 (46.8)	33 (53.2)	0.02	22 (26.8)	60 (73.2)	<0.01
No	126 (56.0)	30 (29.4)	72 (70.6)		14 (11.5)	108 (88.5)	

Table 4. Interaction between the absence of a close positive support network member and sexuality on the odds of injecting within the last 6 months

	Absence of a Close Positive Support Network Member		Presence of a Close Positive Support Network Member		OR (95% CI); for presence versus absence of a close positive support network member within strata of sexuality
	N injected/ did not inject drugs within the last 6 months	OR (95% CI); *P*	N injected/ did not inject drugs within the last 6 months	OR (95% CI); *P*	
Heterosexual	68/27	1.00	16/23	0.24 (0.16-0.37) *<0.0001*	0.24 (0.16-0.37)
Non-Heterosexual	8/5	0.56 (0.30-1.04) *0.07*	13/4	1.40 (0.72-2.69) 0.32	2.50 (1.07-5.78)

* Measure of effect modification on multiplicative scale: ratio of ORs: 0.10

**ORs are adjusted for age, age^2, sex, diagnosis with a mental health condition, and any morphine/Dilaudid/cocaine/heroin/Oxycontin use within the last 6 months.

Table 5. Multivariate regression results for the effect of strong tie characteristics on crack smoking

RECENT CRACK SMOKING		Unadjusted OR (95%)	Adjusted OR (95%)
Presence of a Close Positive Support Network Member	Yes	0.41 (0.17-0.99)	0.69 (0.56-0.85)[a]
	No	Referent	Referent
Presence of a Multiplex Negative Support Network Member	Yes	0.47 (0.40-0.56)	0.39 (0.26, 0.60)[b]
	No	Referent	Referent

[a]ORs are adjusted for injecting within the last 6 months, self-reported anxiety or depression, and any morphine/Dilaudid/cocaine/heroin/Oxycontin use within the last 6 months.
[b]ORs are adjusted for diagnosis with a mental health condition, age, and any morphine/Dilaudid/cocaine/heroin/Oxycontin use within the last 6 months.

Our sample consisted of 155 men and 70 women connected across 10 recruitment trees. 45.3% of our sample had at least high school education, 6.2% had regular work, 47.6% had independent housing and 83.6% were Caucasian (Table 1). The majority (80.0%) reported being heterosexual. The mean age of this sample was 41.4 years old (SD=10.6). 164 of our participants had injected illicit drugs at least once and 204 had smoked crack at least once (Table 2). Many of the participants reported having had a history of mental health illness, with 64.4% having been diagnosed with a mental health condition, and 46.7% reporting depression or anxiety within the last 6 months. Many of the individuals in our sample reported having at least one positive support alter who was “close” (39.6%), multiplex (40.9%), or long-term (44.0%) (Table 3).

Table 1 and Table 2 also show the results of the univariate associations with injecting within the last 6 months and smoking crack within the last 6 months. There appeared to be a significant univariate association between injecting within the last 6 months and gender (p=0.01), age (p=0.03), diagnosis with a mental health condition (p=0.02), popular non-injection drug use within the last 6 months (p<0.01), crack smoking within the last 6 months (p=0.02) and heavy frequent alcohol use (p=0.01). Among individual-level variables, a mental health diagnosis (p<0.01), self-reported depression or anxiety (p=0.02), recent injection (p=0.01) and popular non-injection drug use were found to be significantly associated with recent crack smoking. For social network variables (Table 3), there appeared to be a highly significant univariate association between the presence of a close positive support network member and injecting (p=0.02) as well as crack smoking (p<0.01), presence of a multiplex positive support network member (injecting: p<0.01, crack smoking: p<0.01), and the presence of a long-term positive support network member (injecting: p=0.02, crack smoking p<0.01).

Multivariate models assessing the association between injection and relationship strength were adjusted for age, crack smoking within the last 6 months and popular non-injection drug use within the last 6 months. Models assessing the association between injection and the presence of a multiplex positive support member, multiplex negative support member, or close positive support member also adjusted for sex. Multivariate models assessing the association between crack smoking and strong tie support adjusted for injecting, mental health, and popular drug use; injection drug use was also included in the model assessing the presence of a close positive support member. Likelihood ratio tests showed that sexuality was a significant odds ratio modifier in the relationship between the absence of a close positive support network member and injecting within the last 6 months. Among heterosexuals, those who had a close positive support network member had a 76% lower odds (aOR=0.24, 95% CI: 0.16-0.37) of injecting compared to those who did not have a close positive support member in their network (Table 4). Surprisingly, among non-heterosexuals, having a close positive support network member appeared to be positively associated with one's odds of injecting within the last 6 months (aOR=2.50, 95% CI: 1.07-5.78). Having a close positive support network member was negatively associated with crack smoking, with no interaction with sexuality (aOR=0.69, 95% CI: 0.56-0.85).

Another surprising finding was that the presence of a multiplex negative support network member was found to be protective against recent crack smoking (aOR=0.39, 95% CI: 0.26-0.60), after adjusting for important confounding variables. This was contrary to our hypothesis that having a multiplex negative support network member would increase one's odds of using drugs.

After adjusting for confounding variables, having a long-term support network member was not significantly associated with recently injecting or smoking crack, whether this member was positive or negative.

Discussion

Almost forty per cent of our participants had at least one positive support network member whom they considered 'close.' The presence of a close positive member who provides support in one's social network was associated with a lowered odds of injecting drugs in the last 6 months among those with a history of injecting, but only among heterosexuals. However, regardless of sexuality, having a close positive support network member was associated with a lowered odds of smoking crack within the last 6 months among those with a history of smoking crack. We also found a lowered odds of smoking crack among those with a least one multiplex negative support network member. There appeared to be no significant relationship between drug use and having a positive or negative long-term support network member that engaged in risk behaviours.

What is already known on this topic

Our study confirms the existence of strong-tie network members in the lives of current and past drug-using individuals. This is consistent with studies of male drug users, which showed that people who use drugs do indeed have intimate and stable relationships (25, 27). Kandel found that people who use drugs had even more intimate interpersonal interaction than non-drug users (50, 51), since engaging in drugs together fosters an environment that creates more intimate relationships (52-54). Close relationships often exist as sex partners in the social networks of drug users (55).

Our study also builds on other studies that have looked at the effect of strong ties, support, and peer behaviours on drug use separately. Chitwood et al. found that compared to cocaine users who sought treatment, cocaine users who were not seeking treatment were less likely to have close friends (56). Boyd (1990) studied drug treatment inpatients in an urban setting and found that when asked, "Do you know anyone who would help you get off drugs if you asked?" 30% of men and 17% of women named their mothers. In a study of females in a drug recovery program, about 20% had friends who helped them stop using drugs (57). Moreover, Zapka et al. found that reduced drug use was associated with the number of friends an individual could talk to when upset (58). This work builds on other studies that have shown that social support has a direct impact on healthy adjustment (Cassel, 1976; Sarason et al., 1983; Newcomb & Bentler, 1988) and buffering against stress (59-61). Furthermore, this work adds to other studies which have stressed the association between drug-using peers in one's social environment and individual drug behaviour (62, 63).

What this study adds

The framework presented by Berkman et al. showed that the characteristics of social networks provide opportunities for social support and peer influence, which impact health through health behaviours (18). This is the first study that examines the existence and effect of strong-tie supportive network members on risk behaviours, taking into account the risk behaviours of the network members themselves. The social network approach provides empirical evidence that helps to identify individuals in a drug user's social network that may help with drug cessation. Previous work has been limited to traditional spouse/ partner studies: creating a profile for social network members who naturally aid in the cessation of drug behaviour is useful for public health interventions.

We have found that close positive support network members are associated with a lower odds of recent illicit drug injection among heterosexuals, and crack smoking among both heterosexuals and non-heterosexuals. In the psychological literature, one idea why this may happen is that the inclusion of network members who do not engage in risky behaviours can change one's subjective norms regarding illicit drug use. Subjective norms are beliefs about what others think about a behaviour and whether one should perform it (64). In the Theory of Planned Behavior, subjective norms, along with attitudes about the behavior and perceived behavioural control, dictate one's intention to engage in a behaviour and decision to act on it (64). By having persons who do not engage in drugs or risky sex in their network, a person may be more likely to perceive that these behaviours should not be performed, increasing the pressure to cease smoking crack or injecting drugs. This might especially be true when they consider this person 'close,' which would indicate higher levels of trust and vulnerability to social norms and pressures.

The stress-buffering hypothesis presented by Cohen provides a physiologic mechanism as to why social support can result in positive health outcomes (61). Tangible assistance that close positive support network members can provide, such as money or other material resources, can reduce stress among people recovering from using drugs. This reduction in stress can decrease adverse physiological responses that are emotionally linked, including immune and neuroendocrine processes (65).

However, according to the stress-buffering hypothesis, the receiver must view aid as appropriate—feelings of indebtedness, loss of freedom, or perceived inadequacy can exacerbate stress rather than moderate it (66). This might explain the interesting result of an increased odds of injecting drugs among non-heterosexuals with at least one close positive support network member. In several studies, mothers of HIV-positive gay men were seen as particularly unhelpful because of patterns of intrusive behavior, overprotection and infantilization (67-69). The same pattern may be true among marginalized gay men, regardless of HIV seropositivity: the survival challenges of using drugs or living on the street combined with being a sexual minority could result in greater coddling or overprotective behavior from close loved ones. In addition to inducing stress, close positive support ties might actually represent conflicted relationships for street-involved and drug-using non-heterosexuals. Close positive support ties, such as parents, may feel personal responsibility for their child's homosexuality and their homelessness, leading to overprotection, anger, guilt, and denial (68, 70, 71). This may induce stress rather than moderate it, resulting in greater participation in activities that temporarily alleviate stress, such as injecting drugs.

Why sexuality was found to be an effect modifier for drug injection but not crack smoking is up for interpretation. Individuals who inject and consider themselves non-heterosexual belong to a group that faces daily stigma. Injection drug use is often hidden to avoid ostracism (72) and non-disclosure of sexuality persists for a variety of personal and social reasons (73). However, compared to drug injection, crack-smoking is seen as less 'hard' (74) and smoking rather than injecting can give the user the feeling or appearance of being more 'in control' of their drug use (75). This illusion of being 'in control' may allow people to avoid overprotection or anger from their close positive support network members. Another reason could be simply because the logistic model detects statistical effect modification, which is scale dependent. Had the model been run on an additive scale, effect modification may not have been found.

We did not find that the existence of close or long-term network members who engaged in risk behaviors (i.e., close or long-term negative support network members) were associated recent drug use. There may be a time-related aspect—a network member with whom one has used drugs 20 years ago may not have an effect on their drug patterns now. It is thought that transient, "weak" ties may play a more important role in drug initiation. Valdez, Neaigus, and Kaplan suggest that weak ties, such as those formed by occasional visitation of shooting galleries or gay bathhouses, facilitate the introduction of new drugs and new ways of consuming drugs (76). However, a surprising finding in our study was that the presence of a multiplex negative support network member was associated with a lowered odds of smoking crack within the last 6 months. We suspect that having a network member who is present in several facets of a focal person's life, even if they use drugs, provides an emotional buffer against the hardships of homelessness and marginalization. A multiplex network member is likely to be present in various dimensions of the focal person's life, meaning support is also available as the focal person transitions between different roles and situations (77). Although the presence of a multiplex positive support network member was not found to be significantly associated with crack smoking, we suspect our definition of multiplex may have been limited. A multiplex positive support member could only encompass a kin role and neighbor role. Though we are aware that positive support members could include other roles, these were the only ones we could discern from the survey instrument. Broadening this definition may provide a more substantial depiction of the association between positive support multiplexity and drug use.

We also did not find that long-term positive support members were associated with recent drug use. Again, time may come into play—a network member who has been a permanent fixture in one's life, especially one that has been involved before drug initiation and throughout drug initiation, may be seen as the type of person who will always provide support, regardless of the focal person's behaviour. Thus, long-term support network members may not be as important in eliciting change.

Interventions involving social networks are promising because they take advantage of existing social structures and move the responsibility away from health professionals and institutions (78). Gottlieb suggests that two ways of mobilizing support networks may include: 1) grafting peers onto the current network and 2) enriching current relationships by teaching counseling techniques (78). We could attempt to graft close positive support peers onto the networks of individuals who smoke crack and inject drugs, but this type of social engineering is unfeasible, if not extremely dangerous. Even if we could convince individuals who do not engage in risky behaviours to befriend individuals who use drugs, we could not guarantee that their relationship would develop enough to become close or support-enabling. The act of social engineering itself may be enough to deter these relationships from occurring. Moreover, we could not guarantee that these engineered relationships would not be detrimental for either the support giver or support receiver. We could also enrich current relationships by teaching close positive support network members classical counseling techniques that would encourage their family and/or peers to stop using drugs. By training them in methods that reflect the styles of professional counselors, we run the risk of "professional imperialism" as mentioned by Gottlieb (78). In other words, we assume that the support given by close positive support network members is inadequate when our work has shown that their presence is negatively associated with risk behaviours among their drug-using peers, without receiving counseling techniques.

A more realistic intervention may involve the creation of assistance for existing close positive support network members. The stress of supporting an individual that engages in maladaptive behaviours can take a financial, mental and emotional toll, sometimes resulting in a break of the tie. One example of an intervention that cares for network members are the Alcoholics Anonymous family groups, which help family and friends cope with the challenges of their loved one's drinking behaviour (79). Such a program may be extended to friends and family of people who smoke crack and/or inject drugs.

Limitations of the study

There are several limitations to our study. The first is that respondent driven sampling may produce selection biases from seed selection as well as from recruitment. *Homophily*, a phenomenon that occurs when individuals are more likely to recruit members who are more like themselves, is a problem in all respondent driven sampling studies (80). For example, individuals who use crack may be more likely to recruit other individuals who use crack, making crack use more common in this population. Although we may be able to adjust for some variables that cause homophily, a variety of other immeasurable variables may drive the sampling in directions that we are unable to monitor (81). Also, not only are individuals more likely to recruit persons similar to themselves, but individuals who know more people are also more likely to obtain a recruitment coupon. Thus, there may be a bias toward individuals with a higher number of social ties. The extent to which the respondent driven sample represents the population from which we sought to obtain information is unknown, and currently no method exists that can provide these answers. Despite this, we have performed the analysis using several available methods that attempt to adjust for the biases posed by RDS. We found no significant differences between RDSAT adjusted values and our unadjusted values, and no significant differences between our GEE models and our unadjusted values (see Appendix B). We thus presented the best data we are able to obtain from a population that is extremely difficult to sample, and opted for simpler models to make the limitations of the study transparent. The non-probability and small-sized sample may affect the generalizability of the results, but this is a limitation shared by other RDS studies.

In addition, the study was cross-sectional and for that reason, cannot infer causality. However, as Rothenberg points out, continuous studies with this type of population are structurally and logistically implausible (2006). Furthermore, social desirability may influence individuals to underreport drug use or engagement in risky sex, especially with face-to-face interviews. To minimize this, we chose nurse-interviewers that had extensive experience working with members of this community. Another limitation to the study is the measurement of the social network variables. It is possible that individuals may incorrectly report the nature of their relationships and the behaviors of those in their social network. This limitation is also shared by other epidemiological studies that characterize social networks. We did not control for other social network characteristics, such as the quantity of support. However, a study by Stowe et al. of injection drug users in Sydney found no relationship between the number of support network members and quality of support (82).

It is difficult to tease out what aspect of the relationship is most responsible for eliciting change among people who use drugs, whether it be the fact that the network member is 'close,' the network member does not participate in drugs or risky sex, or the fact that the network member provides instrumental support. Regardless, this is the first study to show that such members do exist in the social networks of drug-using individuals. Moreover, we suspect that the interplay of these characteristics foster the social environment necessary for eliciting behavior change. By recognizing the complexity of relationships that exist among humans, especially those that encourage health-promoting behaviours, we can design interventions that take advantage of social structures and bring individuals who use drugs into recovery.

Conclusion

This is one of the few studies that have examined social network members with whom individuals do not engage in risky sex and who do not participate in drug use. These members can potentially foster an environment where safe, non health-compromising behaviors are the norm. Through peer influences, subjective norms, and stress-buffering, close positive support network members may encourage the cessation of drug behaviours.

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Discussion

In the first manuscript, we conducted a systematic review to determine if multiplexity, closeness, and duration of relationship were associated with risk behaviours, including drug equipment sharing, drug use, and unsafe sex. In the third manuscript we performed a primary analysis of data collected from a marginalized population in Ottawa, Canada and hypothesized that these tie strength measures would be associated with two risk behaviours in particular: injection drug use in the last 6 months and crack use in the last 6 months. We will first discuss the state of vulnerable populations in Canada in comparison to our sample. We will then discuss each of the tie strength variables separately, comparing the findings found in Ottawa with the evidence found in our systematic review.

Sample comparison

Because our research sample was so diverse (sex workers, people who smoke crack, people who inject drugs, homeless individuals), it is difficult to compare our respondent driven sample with others collected in Canada. Moreover, factors such as homophily may have influenced our results in a number of immeasurable ways (1). Despite this, our research is an important snapshot of the current state of vulnerable people in Ottawa and should be considered not only with other studies in Ottawa but in the broader context of Canada.

Between 2008 and 2009 Leonard et al. used convenience sampling to study people who use crack cocaine in Ottawa, ON (2). Similar to our findings, the mean age of the sample was roughly 40, and roughly half had less than high school education (2). Among phase IV findings (May-June 2009, n=251), the ratio of males to females was 75:25(2). The number of participants who injected drugs in the last 6 months was 93 out of 251 (37.1%)(2). Roughly 20% of the sample reported being 'Aboriginal' or 'Other' Ethnicity, which is similar to our own sample (16.4%)(2). The similarity in demographic results gives us greater confidence in our findings.

There is considerable lack of information regarding the homeless in Canada. This is due in part to the inconsistent definition of homelessness, and the difficulty in identifying and communicating with the homeless and poor coordination with local agencies (3, 4). Most available information on the homeless in Canada is available at the municipal level. In 2005, 26% of the Canadian population earned income below what is considered enough to afford a basic home (5). In 2010, 22 276 people accessed shelters in Toronto (6). In 2007, 37% of Toronto's homeless respondents were non-Caucasian, 73% were male, and the average age of males was 39 while the average age of females was 36(7). The male female split is similar to our research done in Ottawa, which was 69:31(7). Similarly, the age demographic is comparable, with our sample yielding an average age of 41.4 years (7). A major difference, however, is in the distribution of race, with only 16% of our participants reporting being non-Caucasian (7). However, this is reflective of regional city differences, with Ottawa having only a 20.2% non-Caucasian population compared with 46.9% in Toronto (8). In Toronto, 17% of the homeless reported having depression and 11% reported having anxiety, compared to our sample (9) in which 46.7% of our participants reported having depression or anxiety. The demographic breakdown of the homeless in Vancouver is similar to Toronto, with 47% being non-Caucasian, 70% being male, and a median age of 40 years (10). 35% of Vancouver's homeless reported having a mental illness, which is closer to the estimate we obtained from our Ottawa sample (10). It is also interesting to note that most of Vancouver's homeless were not accompanied during the survey, which the report asserts is suggestive of a very socially isolated homeless community (10). However, we suspect that homeless individuals, despite being found alone when surveyed, are likely to have a network with whom they have more than casual contact.

Several Canada-wide studies have been conducted for specific target populations, such as street youth and injection drug users. Canada's street youth surveillance program is called the Enhanced Surveillance of Canadian Street Youth (11). The latest report, which surveyed n=4728 youth, has shown that the ratio of males to females is 2:1, which is similar to the Ottawa Social Network Study results (11). Non-Caucasians comprised 37% of the street youth, 73% had used non-injection drugs at least once, and 22% had injected illicit drugs at least once, with cocaine being the drug of choice(11). For youth over 18, 25% reported having completed high school, which is lower than our Ottawa population statistic of 45.3% (11). One third of participants reported experience neglect (11), which may result in poorer mental health outcomes at present and in the future. I-Track, a Public Health Agency of Canada injection drug use surveillance project, collects information on HIV and Hepatitis C using surveys at sentinel sites across Canada. Their latest results show that 72.5% of new HIV cases were male, 8.6% of which is attributed to injection drug use (12). Like our sample, the mean age was 38 years, and roughly half did not complete high school (12). 20% of participants reported borrowing or sharing needles, compared to 12% recorded from our Ottawa sample (12). It is likely that a geographic effect is occurring since Ottawa's size lends itself to funding for the creation of programs that increase access to clean needles, compared to smaller municipalities where such services are scarce (13). More analyses are needed to explain this discrepancy and reduce the national rate of such risk behaviours.

Tie Strength Measures

Closeness

Our study found that homosexuality was a mediator between the existence of a positive close supportive network member and injecting in the last 6 months. Among heterosexuals, the odds of injecting in the last 6 months were reduced by 76% among individuals with a close positive support network member compared to individuals who did not. However, among non-heterosexuals with this type of network member, the odds of injecting in the last 6 months were 2.5 times higher than those without. We discussed the possibility that non-heterosexuals experience unwelcome overprotective behaviours from their close positive support network members which may exacerbate their drug use. We found however, that for both heterosexuals and non-heterosexuals, those with close positive support network members had a 30% lower odds of smoking crack in the last 6 months. We suspect that positive peer influence combined with social support assists former crack smokers in either remaining crack free or transitioning off crack use. Future studies should explore this process further, however, we are the first study to explore a relationship between drug use and close positive support relationships.

Our review demonstrated that closeness was the most studied tie strength measure. Neaigus et al. (2006) was the only author that looked at the transition to injecting in association with closeness (14). The authors found that lower perceived social distance from injectors was inversely associated with transition to injecting (14). The authors assert that this occurs because low perceived social distance still allows for communication promoting injection drug use (14). Our study did not look into the effect of weak-tie social network members; however, we did not find an association between closeness of negative support network members and transition to injection drug use. This null association may speak to the idea that close network members that engage in drug use may not be as important in mitigating the transition to injection drugs—rather, weak ties may be more influential. One possible reason for this is that the hardships of drug dependency may be more visible among close peers, whereas non-close peers, due to less frequent contact, are better able to hide this facet of their lives while promoting injection drug use.

Valente et al. found mixed results regarding closeness and sharing needles. They found that there was a positive association between recent needle sharing and closeness with a friend (15). However, there was no association between recent needle sharing and closeness with a non-friend, nor any association between closeness and non-recent needle sharing behaviour (15). This implies that although close friendships are not important for the transition to injection drugs, they are indeed important in one's immediate choice in sharing needles (15). Similarly, Paquette et al. found that injection drug users in Sydney, Australia had a 3.38 times greater odds of injecting with a close network member (16). HIV risk, a composite of condom behaviour and drug behaviour, was also found to be positively associated with closeness among vulnerable people (17).

Future research should ensure that analyses distinguish between network members who do and do not engage in drugs and risk behaviours. These groups offer different types of peer influence, which can give rise to different types of health behaviours (18).

Multiplexity

We found that the presence of a negative support network member who had multiplex relationships with the respondent was associated with a 60% decreased odds of crack smoking in the last six months among current and former crack smokers. Although this is contrary to our hypothesis that having a risk-taking network member who is present in many facets of a focal person's life would be positively associated with smoking crack, we suspect that the support role played by these individuals may be much more important than previously thought. 31% of individuals who did not smoke crack in the last 6 months reported having at least one negative multiplex member in their network compared to 17% of crack smokers. It is possible that negative support multiplex members, despite the negative peer influence they may exert, provide forms of support that are necessary for avoiding substance use. Simply having one person who can be depended upon for multiple functions (for example, a neighbour with whom one smokes crack but also can be relied upon for a meal or a ride to an appointment) may be protective against the mental and financial hardships of low and unstable income. A similar pattern can be found for individuals with at least one positive support multiplex network member, which were 56% of non-crack smokers versus 32% of crack smokers. Although the presence of this type of network member was not found to be independently associated with crack smoking, our constrained definition of positive support multiplexity may have limited our findings. This definition only included the overlap of kinship and neighbour roles—had we asked more questions about other roles (for example, coworker roles or group/religious affiliation roles), a more substantial depiction of multiplexity may have been found.

Our study was the first to examine a relationship between multiplexity and crack smoking. Our systematic review identified only one multiplexity study, which found a positive association between risky needle use and multiplexity among injection drug users in Los Angeles County, USA (Lakon et al., 2006). The authors assert that overlapping social roles in networks generates social regulation, which occurs when ties control or constrain behaviour (19-21). Social regulation was found to be a mediator in the relationship between needle sharing and multiplexity (21). Thus, injectors may share needles with their peers in order to keep friendships intact (21, 22). We did not have a variable that described social regulation in our survey, however, we suspect that social dynamics may differ between the act of sharing needles and the act of smoking crack. Sharing needles is often performed in the presence of the needle giver or recipient (23), making social regulation more immediate compared to crack smoking, which can be carried out alone (21).

Our analysis of vulnerable people in Ottawa did not find any association between multiplexity and injection within the last 6 months. A possible reason for this finding is that injection drug use works through different pathways. Individuals who use injection drugs rarely initiate their drug use through injection and usually begin their consumption through less invasive modes, such as smoking or snorting (24). By the time an individual transitions to injecting, social mechanisms such as peer influence and social support may no longer be as influential due to addiction and substance dependence. Indeed, many individuals who inject drugs are not encouraged to engage in intravenous drug use by their peers, but rather initiate it out of their own volition (25).

Duration of Relationship

We found no association between length of relationship and injecting drugs or smoking crack, for both positive and negative support network members. This result may speak to the dynamics of social relationships over time. An individual's current behaviours are more heavily dictated by current, short-term relationships since processes such as peer pressure and social regulation are heightened in the course of fostering and sustaining a relationship (26). This is in contrast to longer term relationships, which are more established and do not require behaviour alignment in order for an individual to gain acceptance (17, 26). Bell et al. studied drug users in Houston, Texas and found that length of relationship had no association with HIV risk behaviours (17). The authors noted that relationships do not have to be necessarily long in duration before condom use decreases (27). In fact, initiating condom use during a long-term, committed relationship can signal disloyalty and mistrust (27). Although we suspect that different social processes are at play when comparing condom use and drug use, we believe that aligning behaviour to those of one's peers is more important in a newer relationship rather than one that has endured over time.

Our systematic review did not identify any other studies that addressed the effect of long-term relationships on drug use.

Future Directions and Policy Implications

We have argued that respondent driven sampling is superior to other methods of sampling hidden populations since it is better able to reach some of the most marginalized individuals in society. With this in mind, we encourage the use of respondent driven sampling to obtain needed information from hard-to reach individuals. However, we advise authors to exercise caution when using available estimators to adjust for potential sampling biases posed by respondent driven sampling. It may very well be impossible to adjust for all of the factors that may influence the course of this sampling strategy, and thus we would advise researchers to be transparent about the use of respondent driven sampling in their methods and discussion of study limitations. We would also encourage exploration of respondent driven sampling in longitudinal contexts. Some studies have used respondent driven sampling to recruit cohorts of vulnerable populations and achieved follow-up through extensive tracking information with acceptable loss to follow up rates (28, 29). Longitudinal information can help us determine the direction of causality when studying the behaviours of hard-to-reach populations. Moreover, future work should explore respondent driven sampling as a means of spreading health information and preventing disease. In the Ottawa Social Network study, each participant was tested for HIV using HIV point of care tests. This may be a valuable point of intervention for preventing the spread of illness. Moreover, it may represent an important method of implementing the “Treatment as Prevention” program, wherein populations vulnerable to HIV are sought out, tested, and treated accordingly in order to curb the epidemic (30). The Ottawa Social Network Study has already shown that the first two steps of seeking and treating are achievable through this sampling method. It is possible that a roll-out of the campaign using respondent driven sampling may be successful; more studies are needed to see if this is possible.

Our study demonstrated that tie strength measures such as closeness and multiplexity are associated with recent injection drug use and crack smoking. However, relationships are complex and dynamic, making it difficult to ascertain if these conclusions remain true over time. Moreover, longitudinal methods of capturing these relationships among vulnerable populations have yet to be developed and validated. However, the state of drug users’ relationships in association with their current drug use remains an important question.

The efficacy of educational campaigns aimed at drug cessation and condom use has dwindled since the advent of therapies that have reduced the health impact of HIV/AIDS, and the prevalence of HIV continues to rise (31). Close relationships may be a means by which drug cessation and harm reduction campaigns can be targeted by acting as a pathway between the public health message and the individual at risk. Our study demonstrated that 40% of our sample was in contact with at least one close positive support network member in the last 30 days. We already know that having a close positive support member in one's social network is associated with a 76% lowered odds of injecting within the last 6 months among heterosexuals. We suspect that this occurs through mechanisms such as peer influence and support, and that it is possible to channel health promotion via these social processes.

Canada's National Drug Strategy's Treatment Action Plan aims to enhance access to drug treatment services among those with drug dependencies (32). Approximately $100 million CDN in the span of five years is being invested toward this plan, which involves enabling the RCMP to refer youth to treatment, enhance support for First Nations and Inuit, and provide treatment programs for young offenders with drug dependencies (32). In order to increase access, it may be prudent not only to target the drug-dependent individual, but also their close support-giving family members and friends. These individuals may be key figures in enabling drug dependent individuals to access treatment services outlined by the National Drug Strategy. One example of such an intervention is to support the strong tie network members that are helping an individual through the treatment process, such as educating the network member(s) about medication taken for withdrawal and providing financial aid for transport to outpatient behavioural treatment. In this way, drug dependent individuals are supported by their network members in taking their medication as prescribed, and helped to appointments that can facilitate their recovery. Another intervention may involve facilitating the communication process between the focal person and their network members, such that the perception of overprotection or coddling is reduced. These approaches echo 'family-centered' care, which treats families as participants in healing rather than passive observers (33). It expands upon this approach by not limiting the care to families per se, but to strong ties—this is important as many drug-dependent individuals no longer have contact with family members. However, more research should be done on how to best facilitate this process and how to best provide assistance for support-giving close network members as they utilize time, emotional and financial resources to aid their loved one. Moreover, the National Drug Strategy currently does not have harm reduction as a pillar in its approach (32), despite the fact that many drug-dependent individuals are unwilling or unable to cease their drug use (34). Future research should explore if close positive support network members can act as intermediaries for drug dependent individuals to access harm reduction equipment and services.

Social engineering through networks can be a useful but potentially dangerous means of intervention (35). Thus, we would advise against attempting to create supports within the network, but rather, we encourage the provision of assistance for existing ties in making the recovery or harm reduction process possible.

Conclusion

This research has provided empirical evidence of supportive strong ties in the social networks of vulnerable people and their association with drug and HIV risk behaviour. "Closeness" was found to be particularly associated with drug behaviour among marginalized populations. The combination of social support and peer influence that strong ties provide may be a valuable point of intervention for campaigns aimed at curbing drug dependency, reducing harm, or preventing the spread of HIV, Hepatitis C, and other illnesses. More work must be done on how to best harness the power of these strong ties for program and policy changes. With the help of respondent driven sampling, vulnerable populations can be better studied and accessed not only for information on their needs, but simultaneously providing testing and care. We encourage future work on both social networks and respondent driven sampling to better inform the deliverance of campaigns aimed at reducing the harms of drug dependency and infectious diseases.

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Manuscript II: MA and AJ conceived the manuscript strategy. MA wrote and prepared the manuscript, including execution of the review. AJ supervised the project. TR provided statistical expertise. AJ and TR edited the manuscript.

Manuscript III: MA and AJ conceived the manuscript strategy. AJ designed the survey. MA coordinated the data collection, including collection of surveys, data entry, and data cleaning. MA analysed data with the advice of TR. MA wrote the manuscript. AJ and TR gave conceptual advice and edited the manuscript.

APPENDIX

APPENDIX A: SEARCH STRATEGIES

Embase October 15 2012

1. social network/
2. human relation/
3. social interaction/
4. social support/
5. (relationship* adj3 quality).tw.
6. (relationship* adj3 satisfaction).tw.
7. (tie adj2 strength).tw.
8. intimacy/
9. closeness.tw.
10. (multi?rol* or multi?plex* or multirol* or multiplex*).tw.
11. (relationship* adj3 duration).tw.
12. (relationship* adj3 length).tw.
13. (relationship adj3 stability).tw.
14. (stabl* adj3 relationship*).tw.
15. exp drug dependence/
16. prostitution/
17. homelessness/
18. exp homosexuality/
19. deinstitutionalization/
20. vulnerable population/
21. *at risk populations/ or *homeless/ or *same sex intercourse/ or *prostitution/ or (street youth or homeless youth or injection drug user$ or drug user$ or sex worker$ or prostitute$ or callgirl$ or men who have sex with men or males who have sex with males or women who have sex with women).tw.
22. 1 or 2 or 3 or 4
23. 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14
24. 15 or 16 or 17 or 18 or 19 or 20 or 21
25. 22 and 23 and 24
26. limit 25 to abstracts

Medline October 15 2012

1. exp social environment/ or exp community networks/ or exp social support/
2. Interpersonal Relations/
3. Friends/
4. Family/
5. group processes/ or peer group/
6. (relationship adj3 quality).tw.
7. (relationship adj3 satisfaction).tw.

8. intimacy.tw.
9. closeness.tw.
10. Role/
11. (multi?rol* or multi?plex* or multirol* or multiplex*).tw.
12. (relationship* adj3 duration).tw.
13. (relationship* adj3 length).tw.
14. (stabl* adj3 relationship*).tw.
15. substance-related disorders/ or alcohol-related disorders/ or amphetamine-related disorders/ or cocaine-related disorders/ or inhalant abuse/ or marijuana abuse/ or opioid-related disorders/ or substance abuse, intravenous/
16. Prostitution/
17. exp Homeless Persons/
18. Alcoholics/
19. exp Homosexuality/
20. *at risk populations/ or *homeless/ or *same sex intercourse/ or *prostitution/ or (street youth or homeless youth or injection drug user$ or drug user$ or sex worker$ or prostitute$ or callgirl$ or men who have sex with men or males who have sex with males or women who have sex with women).tw.
21. 1 or 2 or 3 or 4 or 5
22. 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14
23. 15 or 16 or 17 or 18 or 19 or 20
24. 21 and 22 and 23
25. limit 24 to abstracts

PsycINFO October 15 2012

1. exp social networks/ or exp interpersonal interaction/ or social groups/ or social interaction/ or social support/
2. exp relationship quality/
3. exp Relationship Satisfaction/
4. (tie adj2 strength).tw.
5. intimacy/
6. closeness.tw.
7. (multi?rol* or multi?plex* or multirol* or multiplex*).tw.
8. (relationship adj3 duration).tw.
9. (relationship adj3 length).tw.
10. (relationship adj3 stability).tw.
11. (stabl* adj3 relationship*).tw.
12. exp drug addiction/
13. drug dependency/
14. exp drug usage/
15. exp prostitution/
16. exp homeless/ or exp deinstitutionalization/ or exp disadvantaged/
17. same sex intercourse/

18. *at risk populations/ or *homeless/ or *same sex intercourse/ or *prostitution/ or (street youth or homeless youth or injection drug user$ or drug user$ or sex worker$ or prostitute$ or callgirl$ or men who have sex with men or males who have sex with males or women who have sex with women).ti,ab.
19. 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11
20. 12 or 13 or 14 or 15 or 16 or 17 or 18
21. 1 and 19 and 20sociadrupros

CINAHL 21-Oct-2012
(MH "Social Networks")
(MH "Interpersonal Relations") OR (MH "Friendship")
(MH "Support, Psychosocial")
relation* N3 quality
relation* N3 satisfaction
tie N2 strength
(MH "Intimacy")
closeness
(MH "Role+")
multi?rol* or multi?plex* or multirol* or multiplex*
relation* N1 duration
relation* N2 length
stabl* N3 relationship*
relation* N3 stability
(MH "Substance Use Disorders+")
(MH "Substance Dependence+")
(MH "Prostitution")
(MH "Substance Abusers") OR (MH "Homeless Persons")
(MH "Deinstitutionalization")
(MH "GLBT Persons+")
*at risk populations/ or *homeless/ or *same sex intercourse/ or *prostitution/ or (street youth or homeless youth or injection drug user$ or drug user$ or sex worker$ or prostitute$ or callgirl$ or men who have sex with men or males who have sex with males or women who have sex with women)

Sociological Abstracts October 15 2012
SU.EXACT.EXPLODE("Kinship Networks" OR "Social Networks")
SU.EXACT.EXPLODE("Group Dynamics" OR "Social Interaction")
SU.EXACT.EXPLODE("Cliques" OR "Gangs" OR "Peer Groups" OR "Primary Groups" OR "Social Groups")
SU.EXACT.EXPLODE("Social Support")
SU.EXACT("Interpersonal Relations")
SU.EXACT.EXPLODE("Interpersonal Relationship Satisfaction" OR "Marital Satisfaction")
SU.EXACT.EXPLODE("Intimacy")
SU.EXACT.EXPLODE("Family Roles" OR "Occupational Roles" OR "Roles" OR "Sex Roles" OR "Sick Role" OR "State Role" OR "Womens Roles")
SU.EXACT.EXPLODE("Social Equilibrium")
SU.EXACT.EXPLODE("Family Stability")

SU.EXACT.EXPLODE("Drug Addiction")
SU.EXACT.EXPLODE("Alcohol Abuse" OR "Drug Abuse" OR "Drug Addiction" OR "Substance Abuse")SU.EXACT.EXPLODE("Drug Injection")
SU.EXACT.EXPLODE("Drug Use")
SU.EXACT.EXPLODE("Prostitution")
SU.EXACT.EXPLODE("Homelessness")
SU.EXACT.EXPLODE("Deinstitutionalization")
SU.EXACT.EXPLODE("Disadvantaged")
SU.EXACT.EXPLODE("Marginality")

APPENDIX B: ANALYSES OUPUT

INJECTION IN THE LAST 6 MONTHS

POSITIVE CLOSE

Logistic Regression, Imputed

Parameter Estimates						
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**t for H0: Parameter =Theta0**	**Pr > |t|**
intercept	5.536963	1.339076	2.91242	8.16151	4.13	<.0001
age	-0.293147	0.063892	-0.41837	-0.16792	-4.59	<.0001
age*age	0.003080	0.000755	0.00160	0.00456	4.08	<.0001
mcondn	1.079049	0.192815	0.70108	1.45702	5.60	<.0001
big5	1.849238	0.196454	1.46419	2.23428	9.41	<.0001
bi_xclosepos	-1.435187	0.213004	-1.85267	-1.01771	-6.74	<.0001
lgbtq	-0.563200	0.315944	-1.18244	0.05604	-1.78	0.0747
bi_xclosepos* lgbtq	2.650819	0.497080	1.67656	3.62508	5.33	<.0001

Logistic Regression, Unimputed (Listwise deletion, n=156)

Analysis of Maximum Likelihood Estimates							
Parameter			**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept			1	7.6430	3.4994	4.7704	0.0290
bi_xclosepos	**1**		1	-1.4257	0.4755	8.9895	0.0027
age			1	-0.3880	0.1704	5.1851	0.0228
age*age			1	0.00416	0.00204	4.1545	0.0415
mcondn	**1**		1	1.0657	0.4330	6.0587	0.0138
big5	**1**		1	1.7385	0.4427	15.4211	<.0001
lgbtq	**1**		1	-0.6058	0.7135	0.7209	0.3959
bi_xclosepos*lgbtq	**1**	**1**	1	2.6260	1.1115	5.5813	0.0182

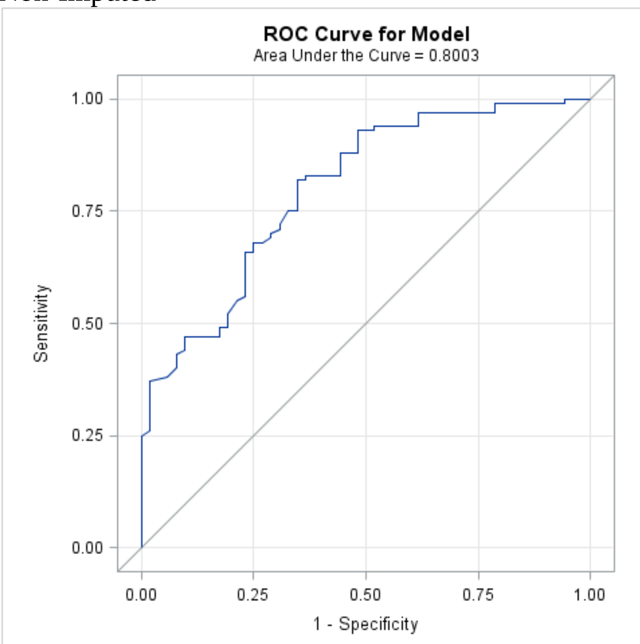
Generalized Estimating Equations (Unimputed)

Analysis Of GEE Parameter Estimates								
Model-Based Standard Error Estimates								
Parameter			**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept			7.6442	3.5728	0.6416	14.6468	2.14	0.0324
age			-0.3808	0.1722	-0.7182	-0.0433	-2.21	0.0270
age*age			0.0041	0.0021	0.0001	0.0081	2.00	0.0457
mcondn	1		1.0120	0.4272	0.1748	1.8492	2.37	0.0178
big5	1		1.6638	0.4324	0.8163	2.5114	3.85	0.0001
bi_xclosepos	1		-1.2661	0.4708	-2.1889	-0.3434	-2.69	0.0072
lgbtq	1		-0.4445	0.7137	-1.8433	0.9543	-0.62	0.5334
bi_xclosepos*lgbtq	1	1	2.3476	1.1160	0.1603	4.5349	2.10	0.0354
Scale			1.0000	.	.	.	.	.

Missing Data Patterns													
Group	**mcondn**	**age**	**lgbtq**	**bi_xclosepos**	**big5**	**recentinjector**	**hsedu**	**income**	**housing**	**sex**	**race**	**Freq**	**Percent**
1	X	X	X	X	X	X	X	X	X	X	X	156	95.12
2	X	.	X	X	X	X	X	X	X	X	X	5	3.05
3	.	X	X	X	X	X	X	X	X	X	X	3	1.83

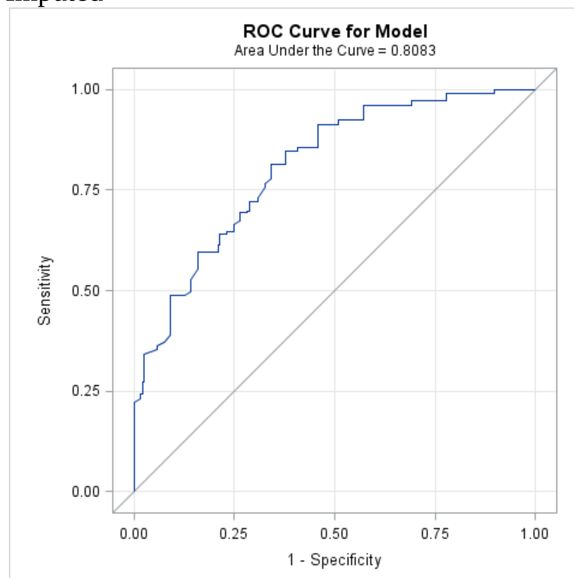
Goodness of Fit Statistics

Non-Imputed



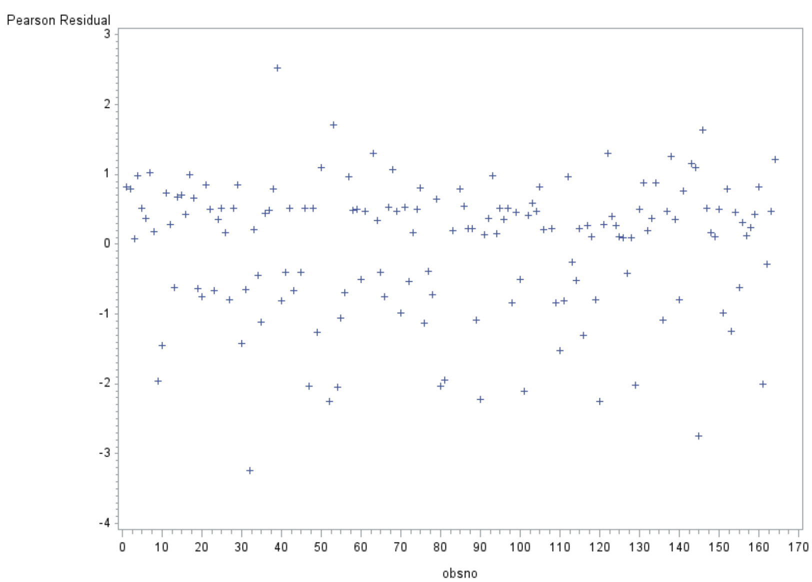
C=0.80
H-L Statistic: p=0.19

Imputed

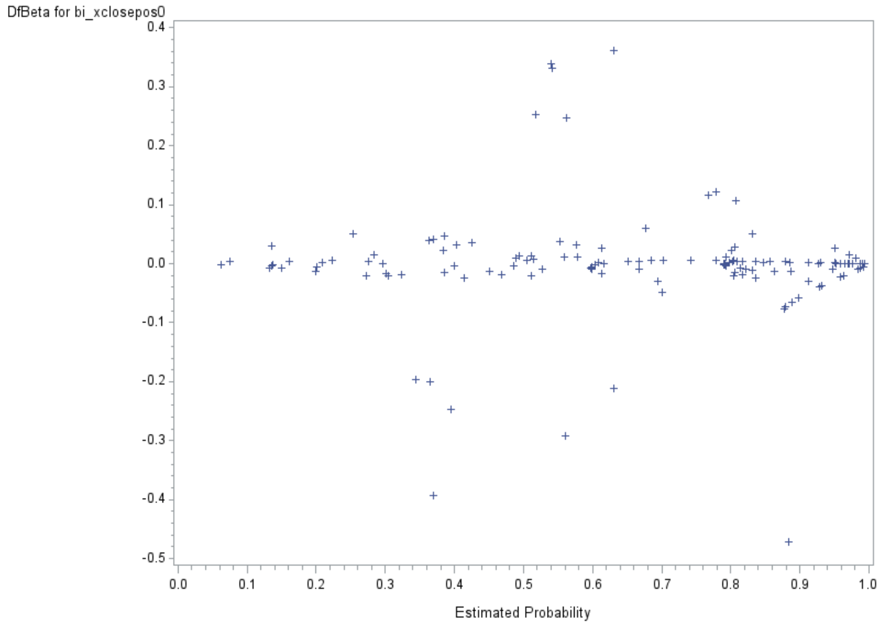


C=0.80
H-L Statistic=0.15

Residual Plots, Unimputed



Dfbetas, Unimputed



POSITIVE MULTIPLEX

Logistic Regression, Imputed

Parameter Estimates					
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**Pr > |t|**
intercept	8.184963	3.452388	1.39334	14.97659	0.0183
bi_xmultipos	-0.740603	0.399010	-1.52265	0.04144	0.0634
age	-0.409798	0.172461	-0.74947	-0.07012	0.0183
age*age	0.004369	0.002049	0.00033	0.00841	0.0342
recentcrsmokerA	0.768952	0.559496	-0.32768	1.86558	0.1693
big5	1.374173	0.423659	0.54382	2.20453	0.0012
sex	0.718478	0.426825	-0.11808	1.55504	0.0923

Logistic Regression, Unimputed (Listwise deletion, n=159)

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	8.8073	3.3669	6.8428	0.0089
bi_xmultipos	**1**	1	-0.7245	0.4038	3.2196	0.0728
age		1	-0.4431	0.1672	7.0223	0.0081
age*age		1	0.00479	0.00198	5.8511	0.0156
recentcrsmokerA	**1**	1	0.8228	0.5595	2.1627	0.1414
big5	**1**	1	1.3364	0.4276	9.7697	0.0018
sex	**1**	1	0.6762	0.4306	2.4661	0.1163

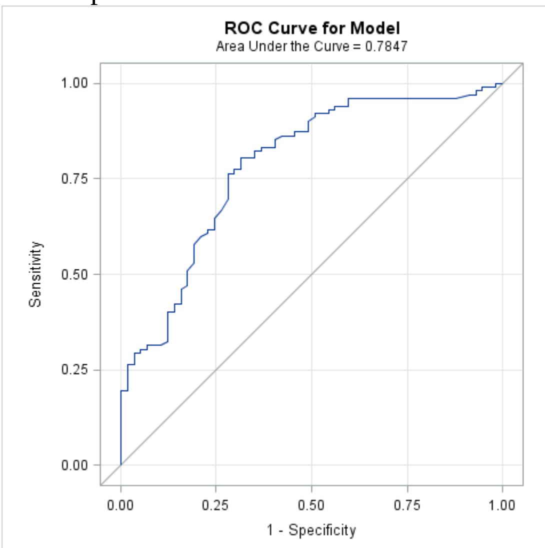
GEE, Unimputed

Analysis Of GEE Parameter Estimates Model-Based Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		8.7360	3.5139	1.8490	15.6230	2.49	0.0129
bi_xmultipos	1	-0.6307	0.4026	-1.4198	0.1584	-1.57	0.1172
age		-0.4264	0.1714	-0.7623	-0.0905	-2.49	0.0128
age*age		0.0046	0.0020	0.0007	0.0086	2.28	0.0224
recentcrsmokerA	1	0.8148	0.5566	-0.2761	1.9058	1.46	0.1432
big5	1	1.2703	0.4134	0.4599	2.0806	3.07	0.0021
sex	1	0.4949	0.4440	-0.3753	1.3652	1.11	0.2650
Scale		1.0000	.	.	.	.	.

Missing Data Patterns												
Group	**bi_xmultipos**	**recentcrsmokerA**	**big5**	**sex**	**age**	**hsedu**	**income**	**lgbtq**	**housing**	**race**	**Freq**	**Percent**
1	X	X	X	X	X	X	X	X	X	X	159	96.95
2	X	X	X	X	.	X	X	X	X	X	5	3.05

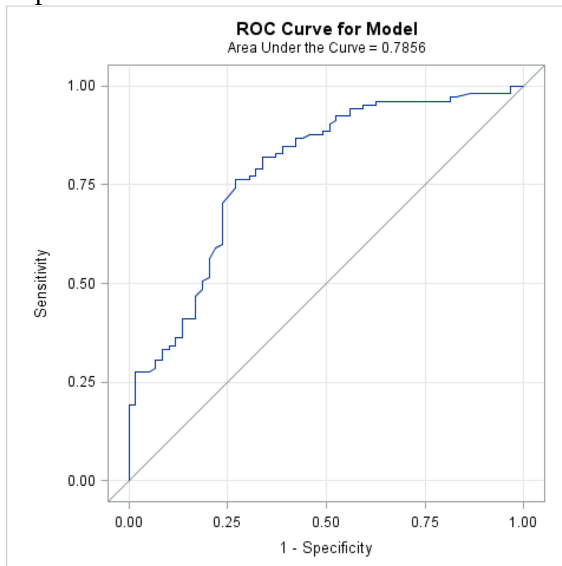
Goodness-of-fit statistics

Non-Imputed



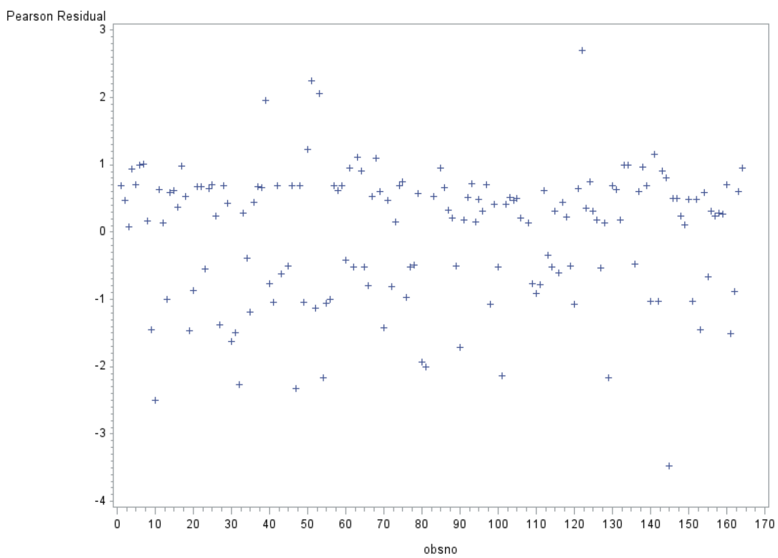
C=0.78
H-L Statistic: p=0.40

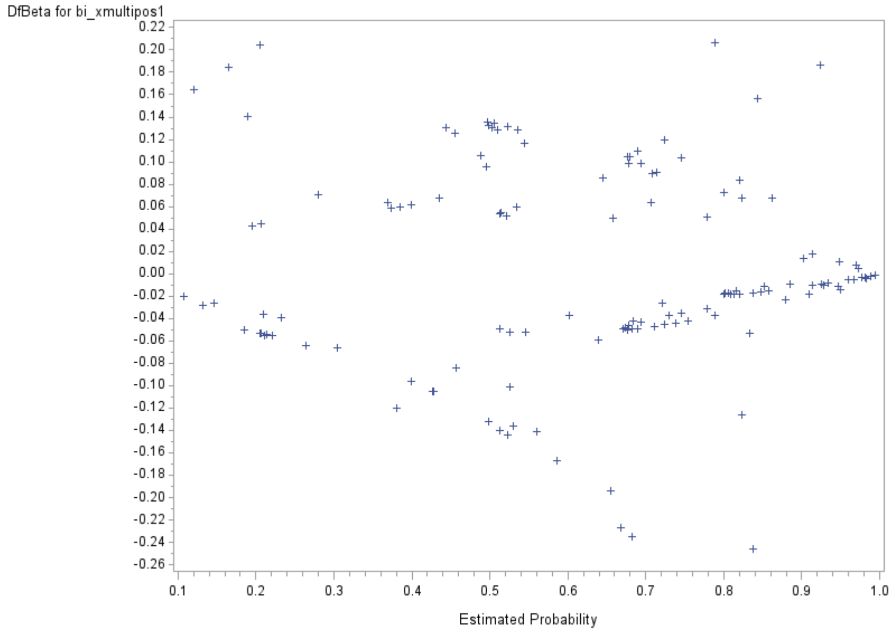
Imputed



C=0.79
H-L Statistic=0.27

Residual plots, unimputed





POSITIVE LONG TERM

Logistic Regression, Imputed

Parameter Estimates						
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**DF**	**Pr > |t|**
bi_xtiepos	0.002129	0.264388	-0.51606	0.520320	357262	0.9936
age	-0.396833	0.231613	-0.89870	0.105031	12.63	0.1111
age*age	0.004234	0.002803	-0.00190	0.010364	11.589	0.1576
recentcrsmokerA	0.332388	0.280738	-0.21803	0.882800	3786.6	0.2365
big5	0.721177	0.215501	0.29879	1.143564	41704	0.0008
lgbtq	0.275004	0.265767	-0.24590	0.795903	113224	0.3008
bi_xtiepos*lgbtq	0.590116	0.271967	0.05696	1.123277	5656.5	0.0301

Logistic Regression, Unimputed

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	10.8406	3.5559	9.2942	0.0023
bi_xtiepos	**1**	1	-0.0125	0.2661	0.0022	0.9625

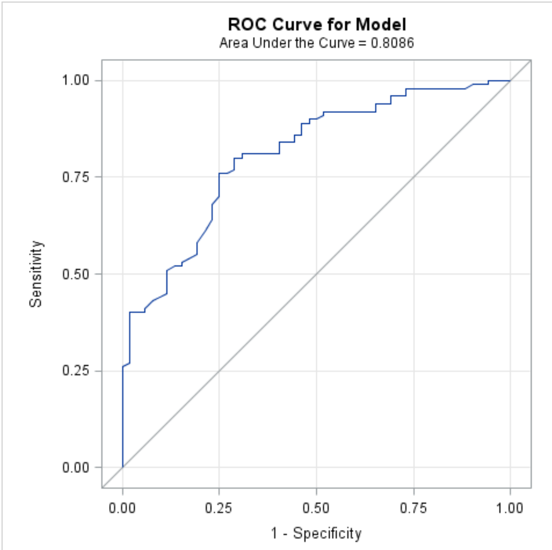
Analysis of Maximum Likelihood Estimates							
Parameter			**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
age			1	-0.4985	0.1743	8.1785	0.0042
age*age			1	0.00550	0.00206	7.1088	0.0077
recentcrsmokerA	**1**		1	0.3573	0.2817	1.6091	0.2046
big5	**1**		1	0.6937	0.2181	10.1164	0.0015
lgbtq	**1**		1	0.2867	0.2673	1.1504	0.2835
bi_xtiepos*lgbtq	**1**	**1**	1	0.6367	0.2725	5.4593	0.0195

GEE, Unimputed

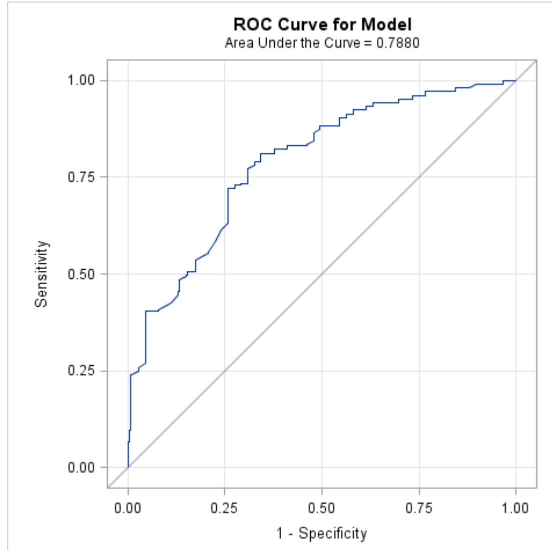
Analysis Of GEE Parameter Estimates Model-Based Standard Error Estimates								
Parameter			**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept			9.8093	3.6000	2.7534	16.8652	2.72	0.0064
bi_xtiepos	1		-1.1396	0.4565	-2.0343	0.2449	1.50	0.125
age			-0.4781	0.1751	-0.8212	-0.1350	-2.73	0.0063
age*age			0.0053	0.0021	0.0012	0.0093	2.56	0.0104
recentcrsmokerA	1		0.6977	0.5652	-0.4100	1.8054	1.23	0.2170
big5	1		1.3491	0.4250	0.5161	2.1821	3.17	0.0015
lgbtq	1		-0.5053	0.7653	-2.0053	0.9947	-0.66	0.5091
bi_xtiepos*lgbtq	1	1	2.2769	1.0904	0.1398	4.4140	2.09	0.0368
Scale			1.0000	.	.	.	.	.

Missing Data Patterns													
Group	**age**	**bi_xtiepos**	**recentcrsmokerA**	**recentinjector**	**big5**	**lgbtq**	**hsedu**	**income**	**housing**	**race**	**sex**	**Freq**	**Percent**
1	X	X	X	X	X	X	X	X	X	X	X	159	96.95
2	.	X	X	X	X	X	X	X	X	X	X	5	3.05

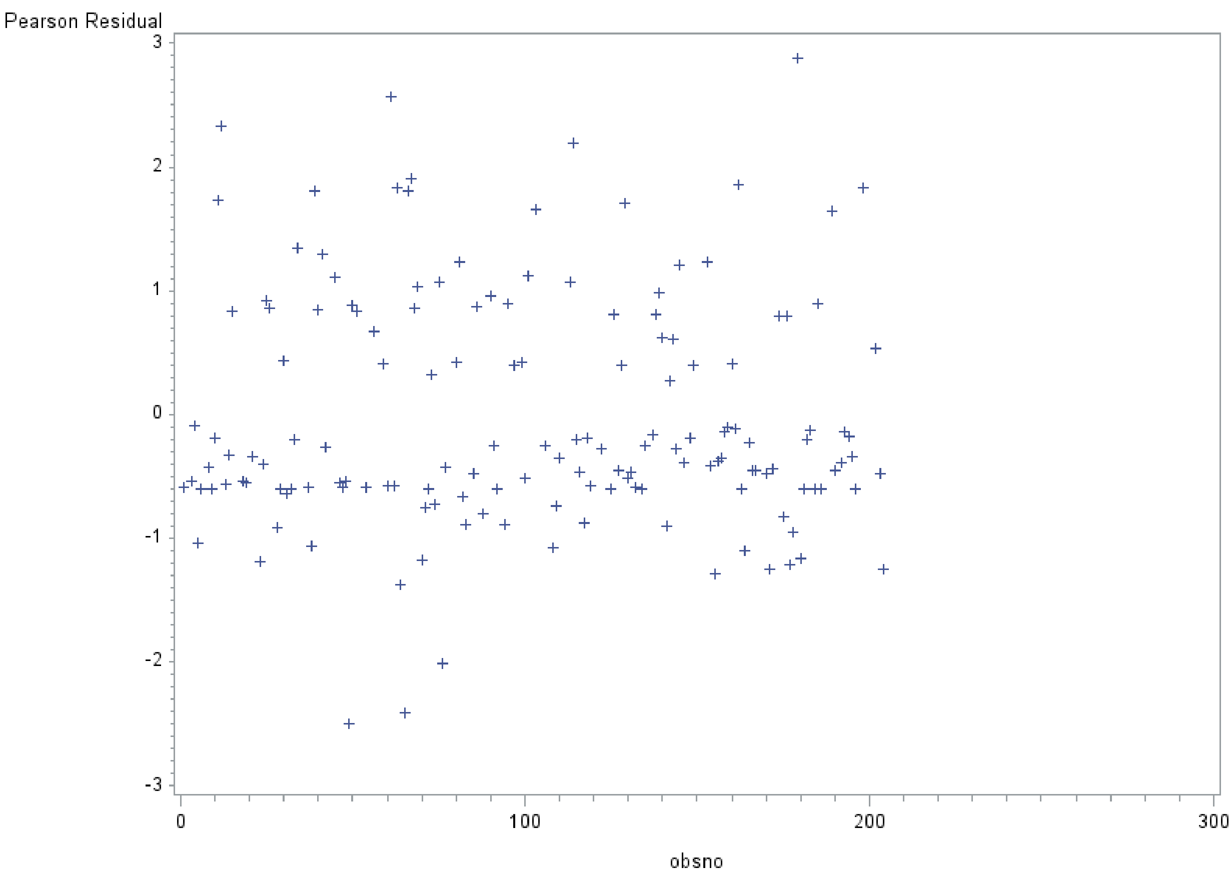
Non-Imputed Imputed

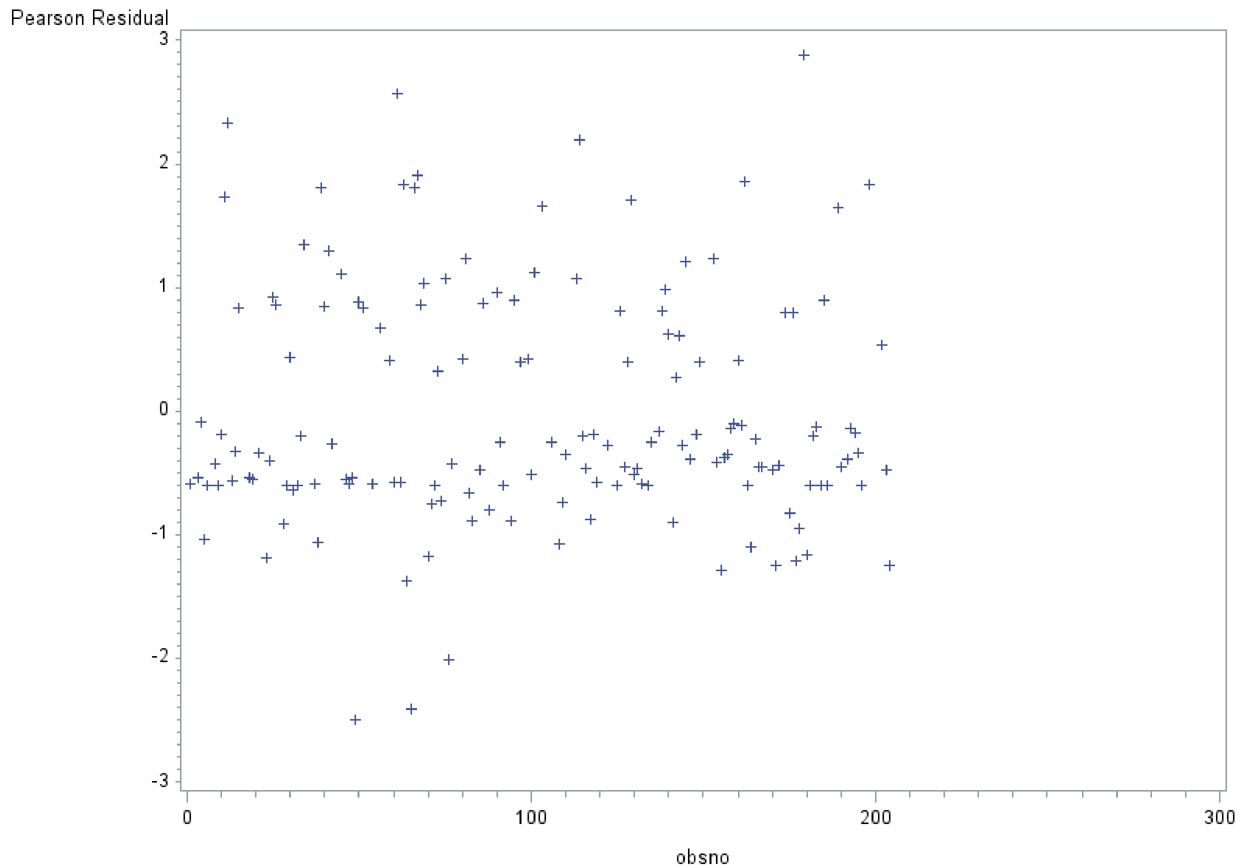


C=0.81
H-L Statistic: p=0.81



C=0.79
H-L Statistic=0.14





NEGATIVE, MULTIPLEX

Logistic regression, imputed

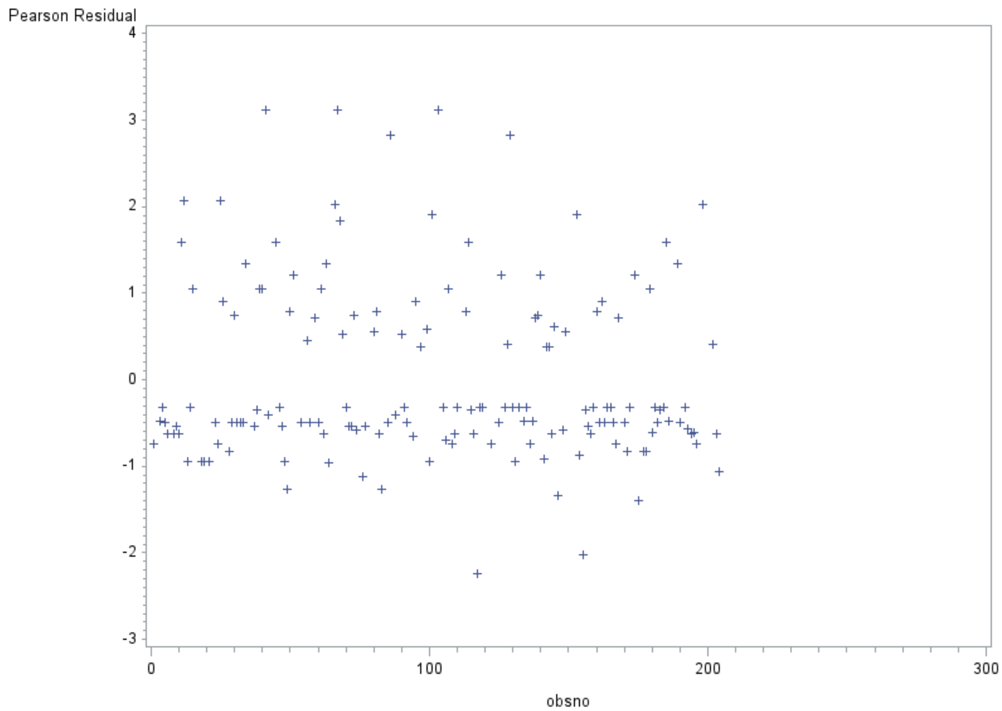
Parameter Estimates						
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**DF**	**Pr > |t|**
intercept	1.571923	0.771573	0.05948	3.08437	9749.6	0.0416
bi_xmultineg	-0.046097	0.497233	-1.02066	0.92846	437684	0.9261
recentcrsmoker	0.012001	0.566015	-1.09785	1.12185	2785.7	0.9831
heavyfreq	0.661071	0.414568	-0.15147	1.47361	3.88E8	0.1108
mcondn	-0.849752	0.432341	-1.69713	-0.00238	2.82E6	0.0494
big5	-1.945005	0.444850	-2.81690	-1.07311	271096	<.0001
sex	-0.779710	0.432795	-1.62797	0.06855	8.61E9	0.0716

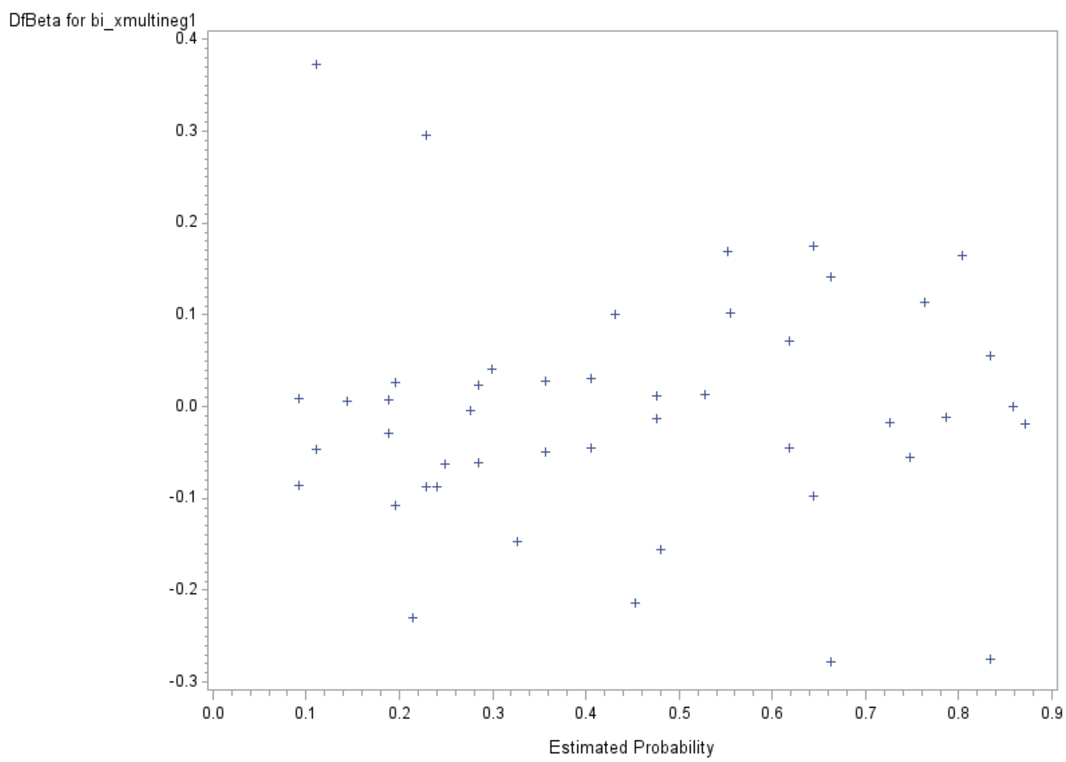
Logistic regression, unimputed

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	1.5879	0.7144	4.9403	0.0262
bi_xmultineg	**0**	1	0.1966	0.4979	0.1559	0.6929
recentcrsmoker	**0**	1	-0.1118	0.5613	0.0396	0.8422
heavyfreq	**0**	1	0.4942	0.4282	1.3315	0.2485
mcondn	**0**	1	-0.8204	0.4378	3.5110	0.0610
big5	**0**	1	-1.8937	0.4524	17.5233	<.0001
sex	**0**	1	-0.8667	0.4419	3.8467	0.0498

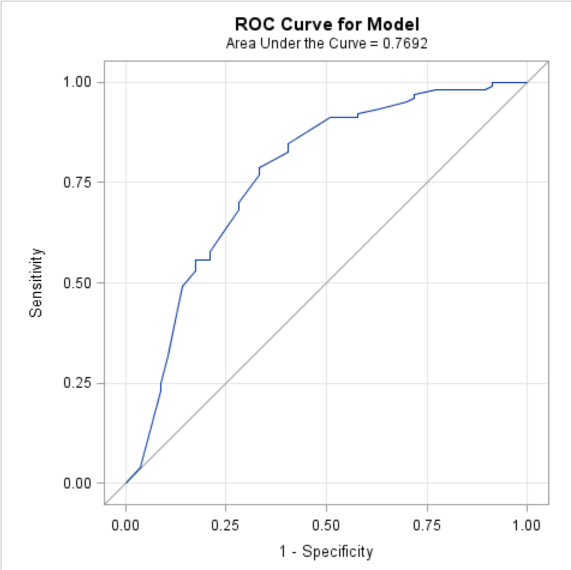
GEE, Unimputed

Analysis Of GEE Parameter Estimates Model-Based Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-0.8747	0.6578	-2.1639	0.4145	-1.33	0.1836
bi_xmultineg	1	-0.0723	0.4870	-1.0268	0.8823	-0.15	0.8820
recentcrsmokerA	1	0.0750	0.5224	-0.9488	1.0988	0.14	0.8858
heavyfreq	1	-0.4581	0.4187	-1.2787	0.3625	-1.09	0.2739
mcondn	1	0.8562	0.4272	0.0190	1.6935	2.00	0.0450
big5	1	1.7482	0.4318	0.9020	2.5945	4.05	<.0001
sex	1	0.5215	0.4530	-0.3663	1.4093	1.15	0.2496
Scale		1.0000	.	.	.	.	.

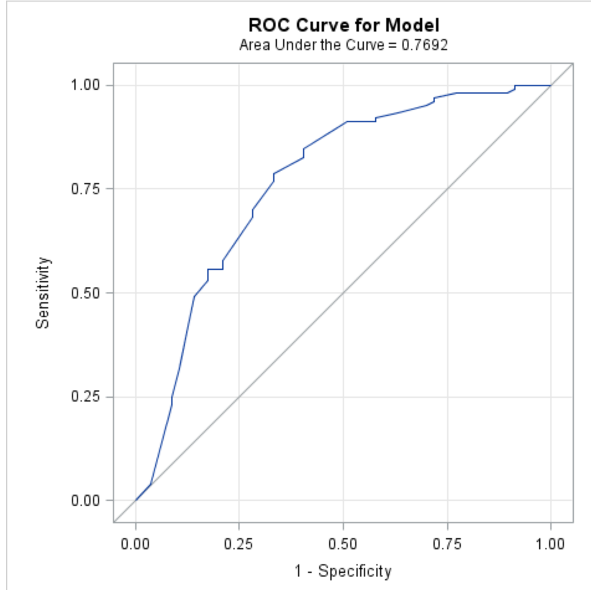




Non-Imputed Imputed



C=0.77
H-L Statistic: p=0.64



C=0.77
H-L Statistic=0.65

CRACK SMOKING IN THE LAST 6 MONTHS

CLOSE, POSITIVE

LOGISTIC REGRESSION, IMPUTED

Parameter Estimates						
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**DF**	**Pr > |t|**
intercept	0.564083	0.208531	0.15536	0.97281	49163	0.0068
bi_xclosepos	-0.746155	0.218756	-1.17491	-0.31740	3.65E6	0.0006
recentinjectorA	0.192314	0.230141	-0.25875	0.64338	5.88E6	0.4034
anxdep	1.109003	0.238348	0.64184	1.57617	65852	<.0001
big5	1.561382	0.230074	1.11044	2.01232	9.47E6	<.0001

LOGISTIC REGRESSION, UNIMPUTED

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	0.7052	0.3667	3.6985	0.0545
bi_xclosepos	**1**	1	-1.0807	0.4178	6.6923	0.0097
recentinjectorA	**1**	1	0.1280	0.4644	0.0760	0.7828
anxdep	**1**	1	0.9481	0.4440	4.5594	0.0327
big5	**1**	1	1.7543	0.4562	14.7863	0.0001

GEE, UNIMPUTED

Analysis Of GEE Parameter Estimates

Model-Based Standard Error Estimates

Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept		0.5542	0.4581	-0.3437	1.4521	1.21	0.2264
bi_xclosepos	1	-0.9336	0.3903	-1.6985	-0.1687	-2.39	0.0167
recentinjectorA	1	0.1251	0.4191	-0.6963	0.9466	0.30	0.7653
anxdep	1	0.9677	0.4056	0.1727	1.7627	2.39	0.0170
big5	1	1.4461	0.4168	0.6292	2.2631	3.47	0.0005
Scale		1.0000	.	.	.	.	.

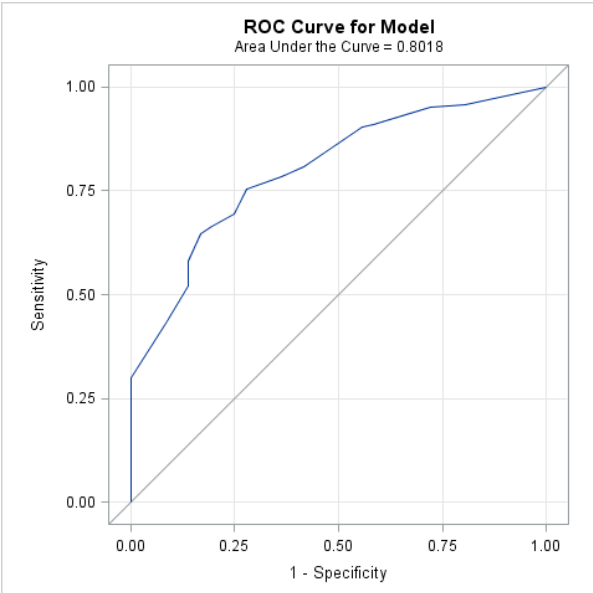
Missing Data Patterns

Group	age	bi_xclosepos	recentcrsmokerA	recentinjectorA	big5	lgbtq	hsedu	income	housing	race	sex	anxdep	Freq	Percent
1	X	X	X	X	X	X	X	X	X	X	X	X	790	99.37
2	X	X	X	X	X	X	X	X	X	X	X	.	5	0.63

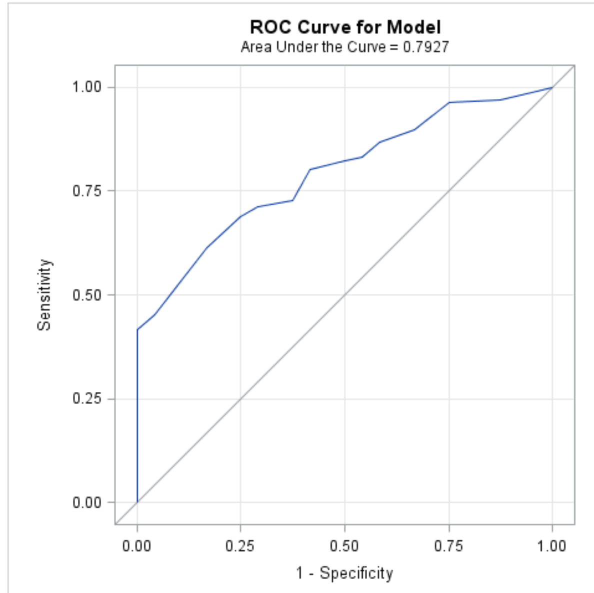
Goodness-of-fit statistics

Non-Imputed

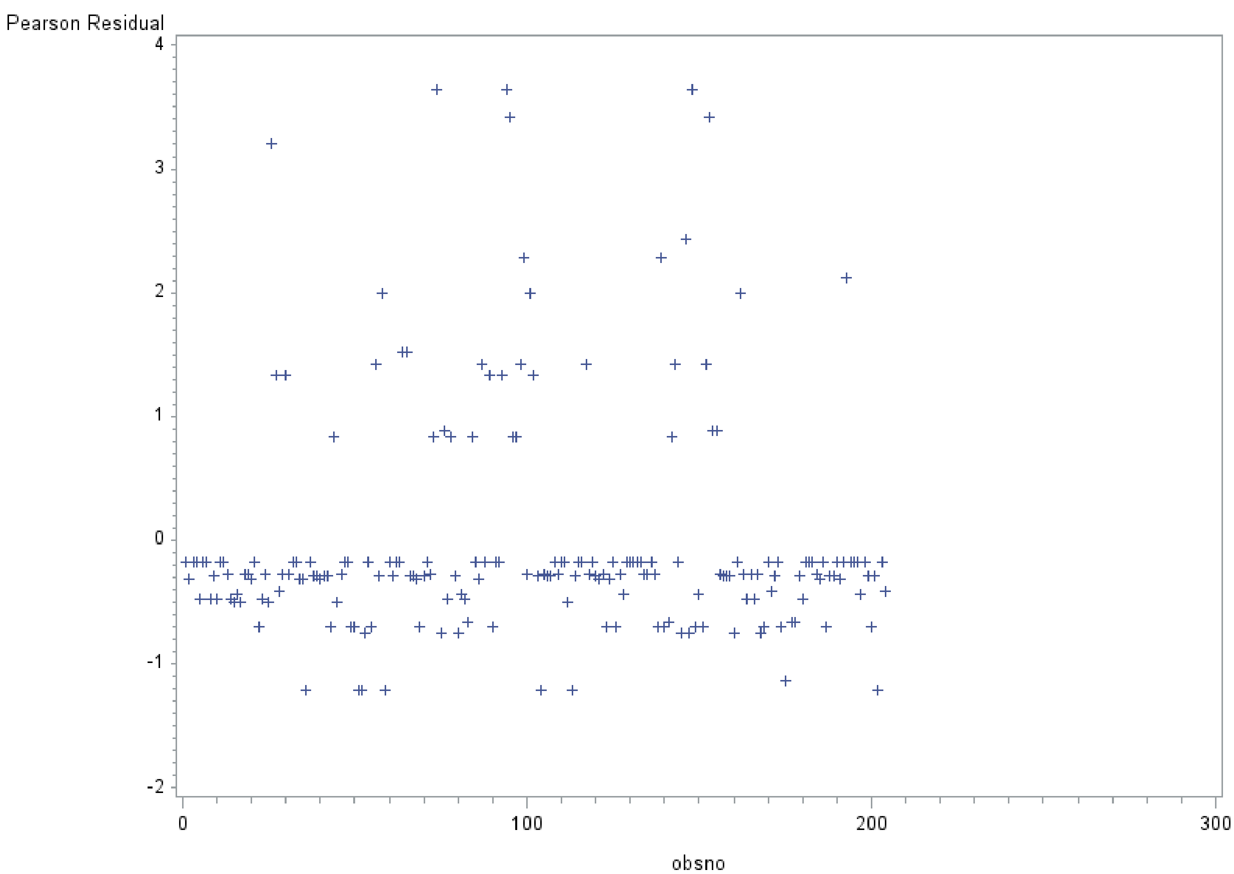
Imputed

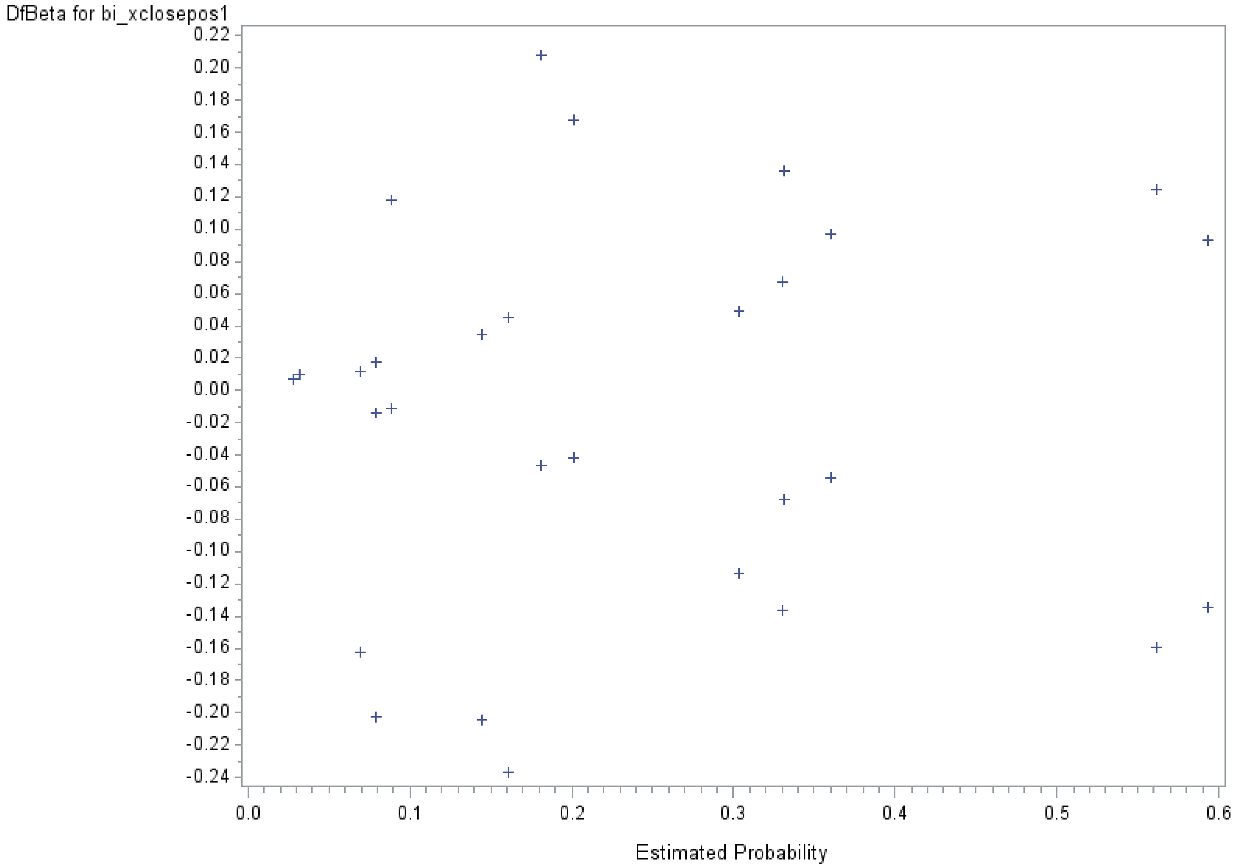


C=0.80
H-L Statistic: p=0.74



C=0.79
H-L Statistic=0.19





MULTIPLEX, POSITIVE

LOGISTIC REGRESSION, IMPUTED

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	0.8158	0.3577	5.2007	0.0226
bi_xmultipos	**1**	1	-0.6358	0.4070	2.4402	0.1183
big5	**1**	1	1.8025	0.4491	16.1100	<.0001
recentinjectorA	**1**	1	0.1883	0.4576	0.1694	0.6807

LOGISTIC REGRESSION, UNIMPUTED (SAME AS IMPUTED, NO MISSING VALUES EXCEPT AGE, WHICH IS NOT INCLUDED IN THE MODEL)

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	0.8158	0.3577	5.2007	0.0226
bi_xmultipos	**1**	1	-0.6358	0.4070	2.4402	0.1183
big5	**1**	1	1.8025	0.4491	16.1100	<.0001
recentinjectorA	**1**	1	0.1883	0.4576	0.1694	0.6807

GEE, UNIMPUTED

Analysis Of GEE Parameter Estimates

Model-Based Standard Error Estimates

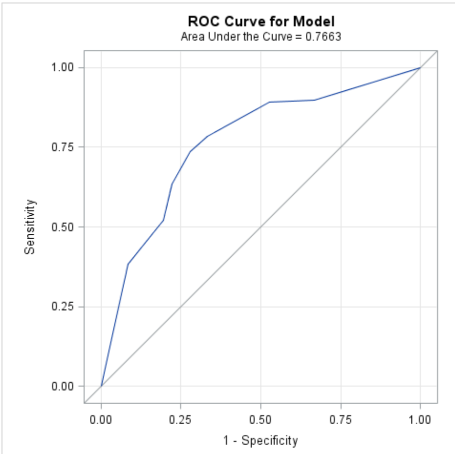
Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept		0.7021	0.4354	-0.1512	1.5554	1.61	0.1068
bi_xmultipos	1	-0.4753	0.3881	-1.2360	0.2854	-1.22	0.2207
big5	1	1.5740	0.4276	0.7360	2.4121	3.68	0.0002
recentinjectorA	1	0.2028	0.4297	-0.6393	1.0450	0.47	0.6369
Scale		1.0000	.	.	.	.	.

Missing Data Patterns

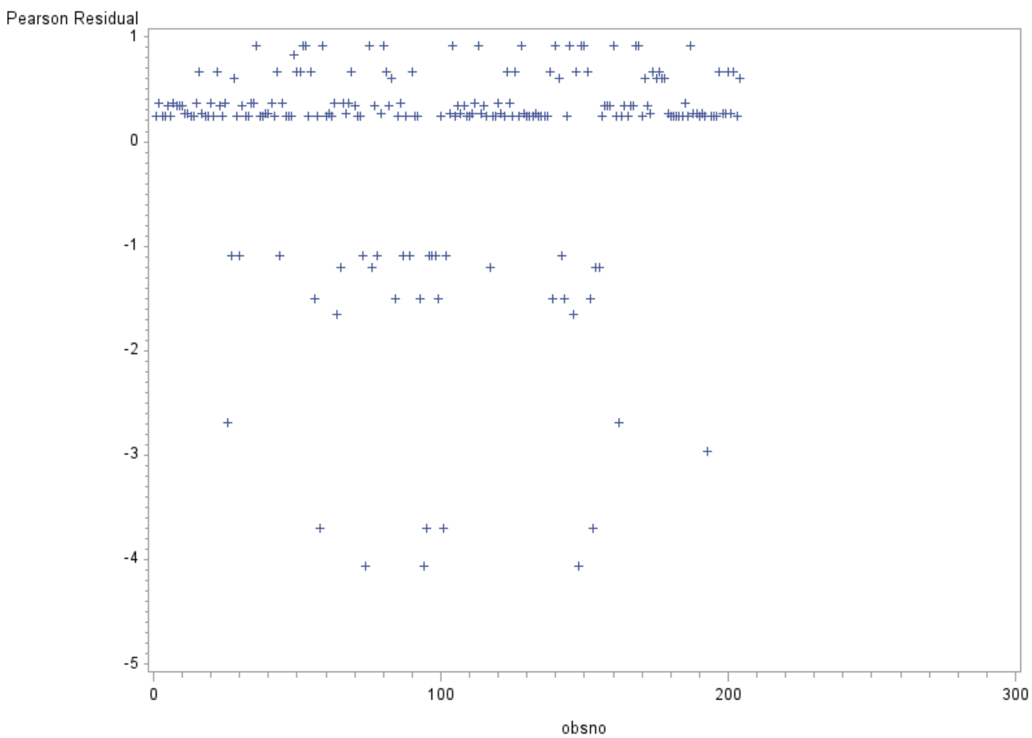
Group	age	bi_xmultipos	recentinjectorA	recentcrsmokerA	big5	lgbtq	hsedu	income	housing	race	sex	anxdep	Freq	Percent
1	X	X	X	X	X	X	X	X	X	X	X	X	196	96.08
2	X	X	X	X	X	X	X	X	X	X	X	.	1	0.49
3	.	X	X	X	X	X	X	X	X	X	X	X	7	3.43

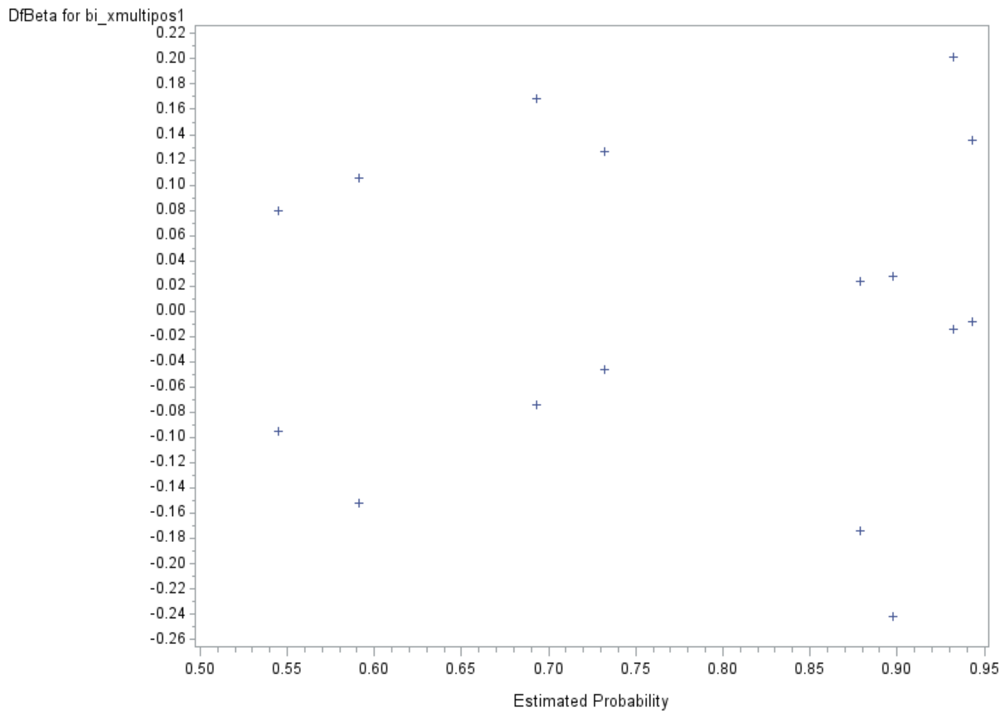
Goodness-of-fit statistics

Non-Imputed (no missing)



C=0.77
H-L Statistic: p=0.35





POSITIVE, LONG TERM

LOGISTIC REGRESSION, IMPUTED

Parameter Estimates					
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**Pr > |t|**
intercept	-0.481722	1.201357	-2.83668	1.873238	0.6884
bi_xtiepos	-0.723844	0.425653	-1.55811	0.110420	0.0890
big5	2.063210	0.491064	1.10074	3.025678	<.0001
age	0.044769	0.022397	0.00085	0.088685	0.0457
sex	0.753803	0.522168	-0.26963	1.777233	0.1489
cannabis6	-0.904655	0.575756	-2.03312	0.223806	0.1161
recentinjectorA	0.091741	0.507317	-0.90258	1.086064	0.8565

LOGISTIC REGRESSION, UNIMPUTED

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	0.0671	1.2554	0.0029	0.9574

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
bi_xtiepos	**1**	1	-0.8845	0.4359	4.1168	0.0425
big5	**1**	1	2.0283	0.4959	16.7286	<.0001
age		1	0.0402	0.0224	3.2256	0.0725
sex	**1**	1	0.6972	0.5269	1.7511	0.1857
cannabis6	**1**	1	-1.1991	0.6271	3.6561	0.0559
recentinjectorA	**1**	1	0.0488	0.5146	0.0090	0.9245

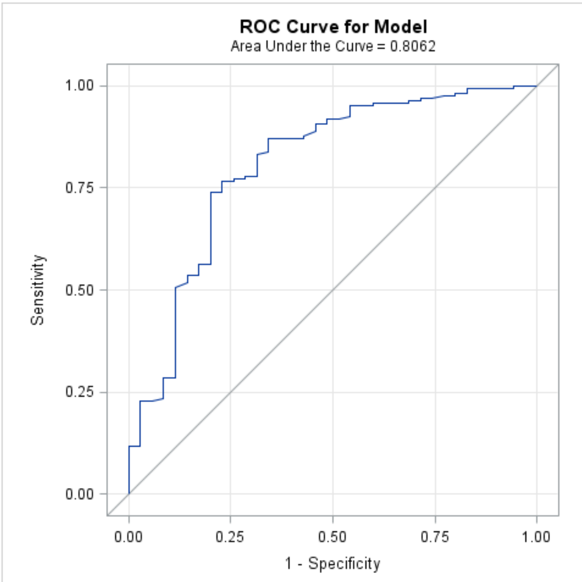
GEE, UNIMPUTED

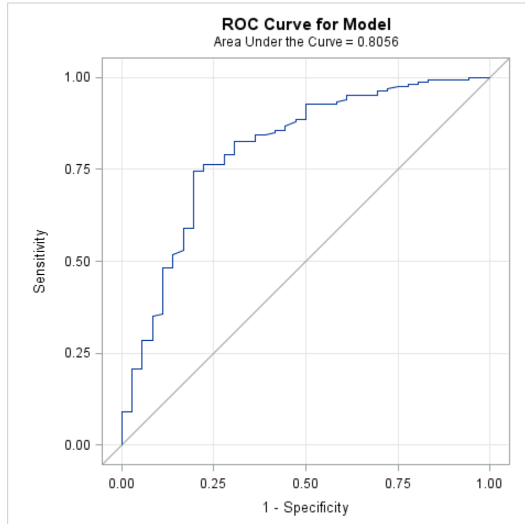
Analysis Of GEE Parameter Estimates Model-Based Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		0.2362	1.2184	-2.1519	2.6243	0.19	0.8463
bi_xtiepos	1	-0.7807	0.4232	-1.6103	0.0488	-1.84	0.0651
big5	1	1.8574	0.4832	0.9103	2.8045	3.84	0.0001
age		0.0354	0.0217	-0.0071	0.0779	1.63	0.1021
sex	1	0.7028	0.5157	-0.3080	1.7136	1.36	0.1730
cannabis6	1	-1.1993	0.6132	-2.4011	0.0025	-1.96	0.0505
recentinjectorA	1	0.0514	0.4916	-0.9120	1.0148	0.10	0.9167
Scale		1.0000	.	.	.	.	.

Missing Data Patterns													
Group	**bi_xtiepos**	**big5**	**cannabis6**	**recentinjectorA**	**sex**	**age**	**hsedu**	**income**	**lgbtq**	**housing**	**race**	**Freq**	**Percent**
1	X	X	X	X	X	X	X	X	X	X	X	197	96.57
2	X	X	X	X	X	.	X	X	X	X	X	7	3.43

Goodness-of-fit statistics

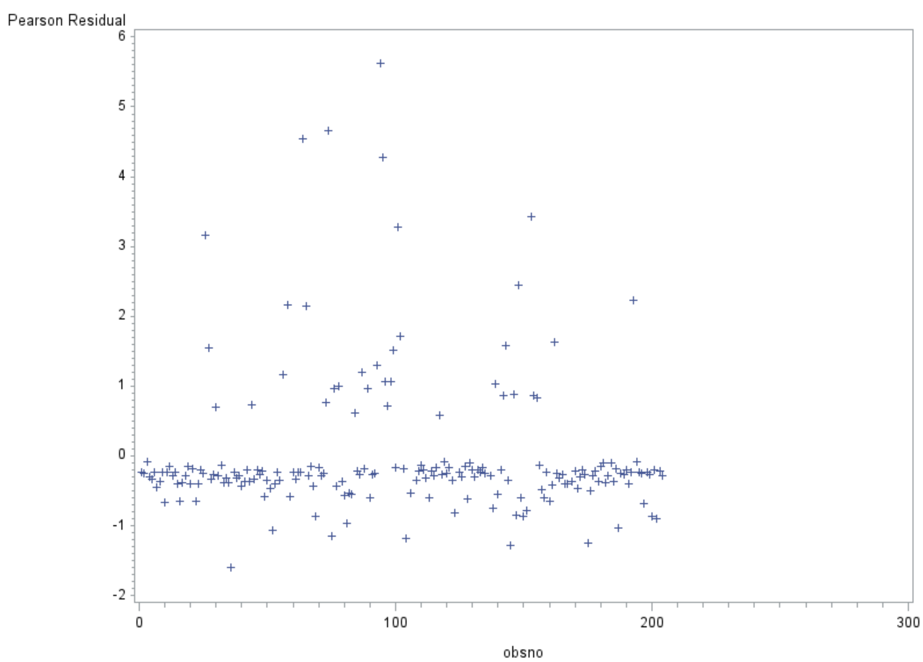
Non-Imputed Imputed

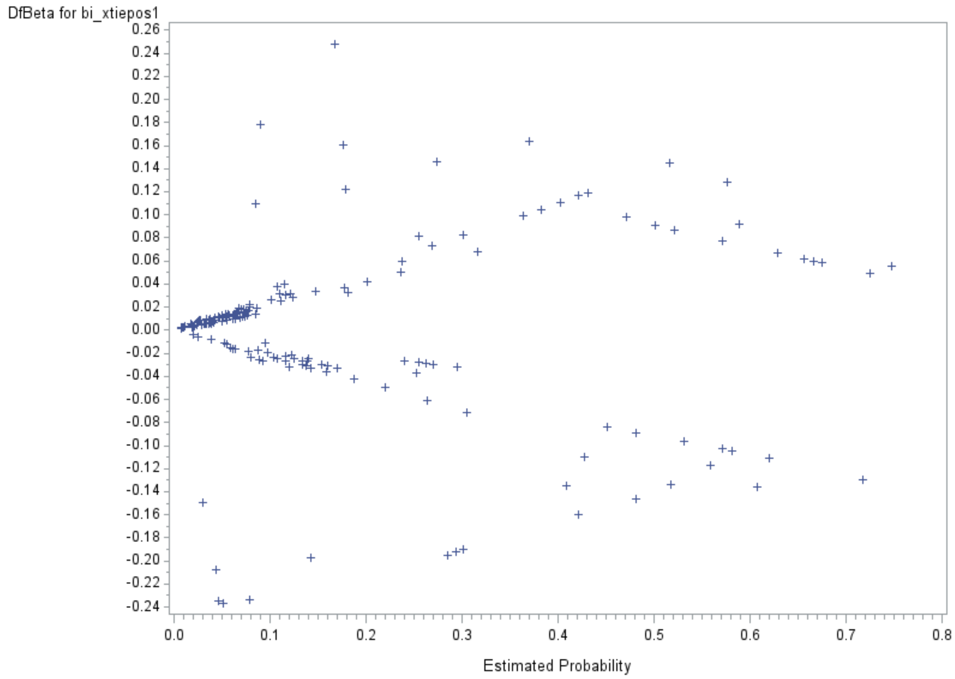




C=0.81
H-L Statistic: p=0.50

C=0.81
H-L Statistic=0.97





NEGATIVE, MULTIPLEX

LOGISTIC REGRESSION, IMPUTED

Parameter Estimates					
Parameter	**Estimate**	**Std Error**	**95% Confidence Limits**		**Pr > |t|**
interceptIntercept	-1.792440	0.425649	-2.62670	-0.95818	<.0001
bi_xmultineg 1 vs,0	-0.921834	0.212953	-1.33921	-0.50445	<.0001
big5 1 vs.0	2.199710	0.199487	1.80872	2.59070	<.0001
ageAge	0.046446	0.009207	0.02840	0.06449	<.0001
mcondnMcondn 1 vs,0	0.867267	0.202594	0.47013	1.26441	<.0001

LOGISTIC REGRESSION, UNIMPUTED

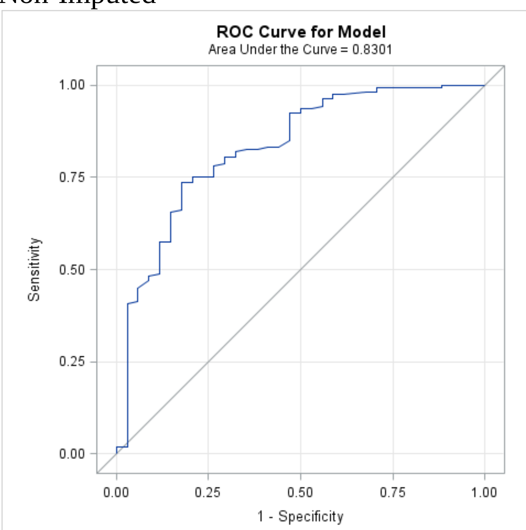
Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-2.8862	1.1173	6.6733	0.0098
bi_xmultineg	**0**	1	0.9876	0.4967	3.9530	0.0468
big5	**1**	1	2.1801	0.4561	22.8429	<.0001
mcondnMcondn	**1**	1	0.9195	0.4561	4.0638	0.0438

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
ageAge	1	0.0486	0.0213	5.2283	0.0222

Missing Data Patterns													
Group	**age**	**lgbtq**	**bi_xmultineg**	**big5**	**recentcrsmoker**	**hsedu**	**income**	**housing**	**sex**	**race**	**mcondn**	**Freq**	**Percent**
1	X	X	X	X	X	X	X	X	X	X	X	194	95.10
2	X	X	X	X	X	X	X	X	X	X	O	3	1.47
3	.	X	X	X	X	X	X	X	X	X	X	7	3.43

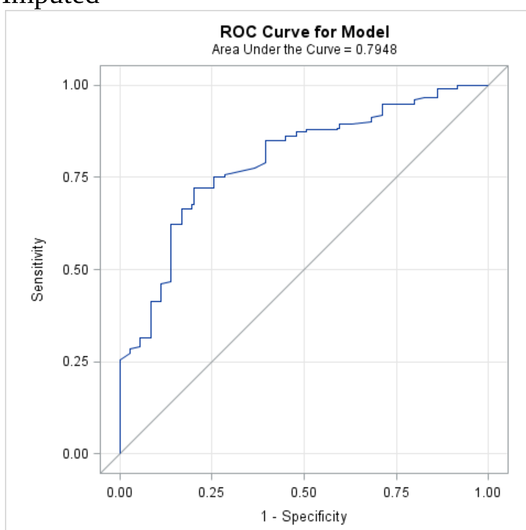
Goodness-of-fit statistics

Non-Imputed



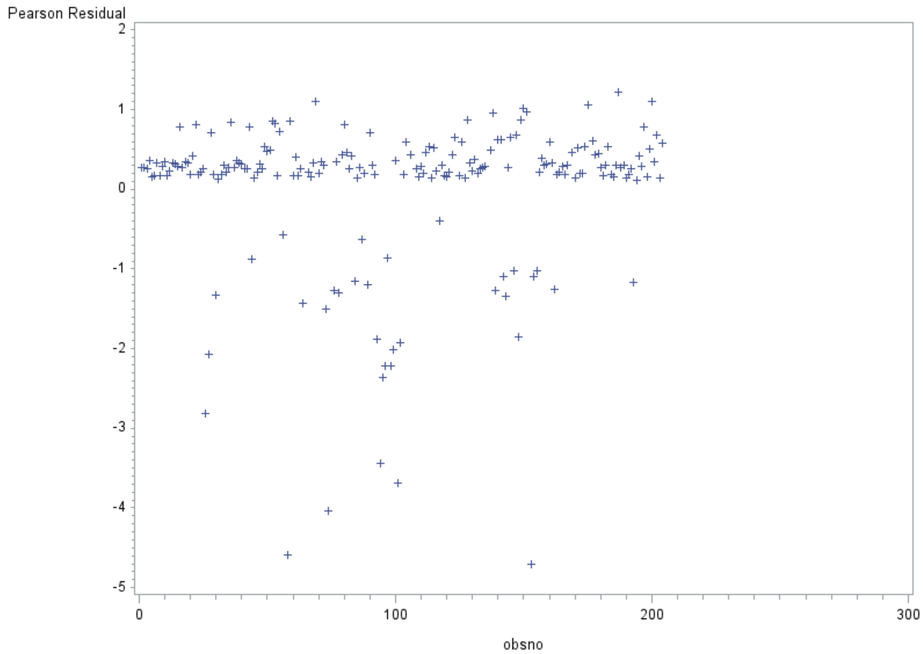
C=0.83
H-L Statistic: p=0.50

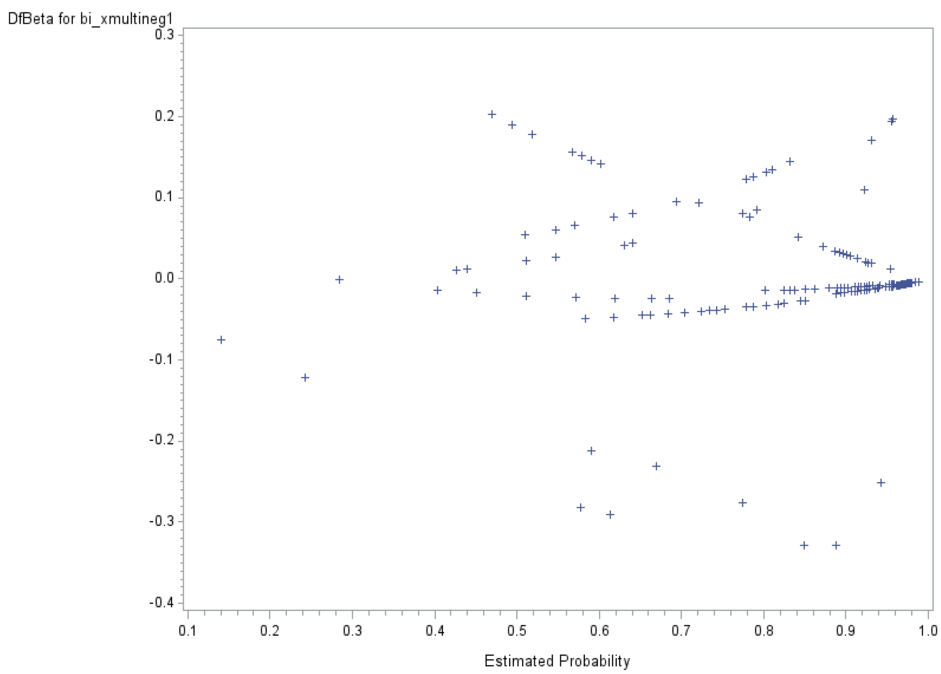
Imputed



C=0.79
H-L Statistic=0.47

DFBETAS


Pearson Residual
2
1
0
-1
-2
-3
-4
-5
0
100
200
300
obsno


DfBeta for bi_xmultineg1
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Estimated Probability