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A Social Network–Informed Latent Class Analysis of Patterns of Substance Use, Sexual Behavior, and Mental Health: Social Network Study III, Winnipeg, Manitoba, Canada

Suellen Hopfer, PhD, Xianming Tan, PhD, and John L. Wylie, PhD

Infection with HIV and other sexually transmitted and bloodborne infections (STBBIs) has been described as occurring in a nexus of risk, in which a diverse range of life circumstances interact to create a risk environment.¹ This nexus-of-risk concept is similar to the social epidemiology literature, which seeks to better understand how individual, social, and structural factors create a risk environment conducive to disease transmission.² In addition to their contribution to understanding risk, contextual approaches of this type are important for developing targeted, effective public health interventions. The efficacy of structural HIV prevention interventions is largely determined by whether the social and structural factors underlying transmission are accurately identified.^{3–5} Further, interventions focused on individual-level behaviors are likely to be more effective when, rather than targeting an entire population with a universal message, they develop communications that resonate with a population subgroup's particular needs.⁶

Specific statistical techniques facilitate identification of subgroups in social contextual analyses. Latent class analysis (LCA) has proven its worth as an inductive technique that uncovers underlying (latent) profiles or classes of individuals with shared characteristics.^{7,8} To date, LCA has been applied in several analyses relevant to STBBI risk. Alcohol abuse has been examined in relation to place of consumption,⁹ sexual behavior,¹⁰ and mental disorders.¹¹ Investigations of illicit drug use have focused on profiles associated with specific substances or groups of substances,^{12,13} with some investigators incorporating routes of administration.^{6,14–16} Higher-order social and structural factors, analogous to the concept of the nexus of risk, have been incorporated to assess HIV risk in relation to homelessness, incarceration, income level, and housing.⁵ Smith and Lanza have brought in elements of an individual's

Objectives. We assessed whether a meaningful set of latent risk profiles could be identified in an inner-city population through individual and network characteristics of substance use, sexual behaviors, and mental health status.

Methods. Data came from 600 participants in Social Network Study III, conducted in 2009 in Winnipeg, Manitoba, Canada. We used latent class analysis (LCA) to identify risk profiles and, with covariates, to identify predictors of class.

Results. A 4-class model of risk profiles fit the data best: (1) solitary users reported polydrug use at the individual level, but low probabilities of substance use or concurrent sexual partners with network members; (2) social–all-substance users reported polydrug use at the individual and network levels; (3) social–noninjection drug users reported less likelihood of injection drug and solvent use; (4) low-risk users reported low probabilities across substances. Unstable housing, preadolescent substance use, age, and hepatitis C status predicted risk profiles.

Conclusions. Incorporation of social network variables into LCA can distinguish important subgroups with varying patterns of risk behaviors that can lead to sexually transmitted and bloodborne infections. (*Am J Public Health.* 2014; 104:834–839. doi:10.2105/AJPH.2013.301833)

social network to compare theorized network roles with those observed empirically, with the intent to inform opinion leader interventions focused on HIV.¹⁷

To our knowledge, the analysis by Smith and Lanza is the only LCA concerning HIV and STBBIs to incorporate aspects of social networks.¹⁷ Their analysis focuses on the potential influence of social network roles as underlying determinants of the success of HIV interventions. We used social network variables of substance use and sexual behavior to assess whether a meaningful set of subgroups could be identified. An approach of this kind could ultimately provide a more nuanced understanding of risk as well as inform the development of more effective prevention programs.

METHODS

We used data from Social Network Study III, carried out in inner-city populations in Winnipeg, Manitoba, Canada, from January to

December 2009. The overall study measured social interaction patterns between members of populations considered at higher risk for STBBIs. We collected data with a nurse-administered questionnaire. Data elements consisted of individual behaviors as well as the respondent's egocentric network (to a maximum of 10 network members). To aid network generation, we prompted participants to think of close contacts, such as friends, relatives, and people with whom they had used drugs, engaged in sexual intercourse, resided, or hung out.

We recruited participants by respondent-driven sampling; study staff selected 22 individuals as seeds (persons known by the staff to be socially connected to inner-city populations engaged in behaviors relevant to Social Network Study III), who distributed coupons to potential participants. In accordance with our ethics approval, we imposed a lower age limit for participation of 14 years. When persons without a coupon contacted the nurse, we

designated them as additional seeds for initiation of new recruitment chains. Following administration of the study questionnaire, we instructed participants to recruit other friends or family who they believed practiced some of the risk behaviors they had been questioned about.

Coupon distribution was voluntary; we provided no secondary incentives. We obtained written informed consent and provided an honorarium to all study participants (Can\$40). A total of 600 participants completed the questionnaire.

Measures

Demographic variables. We categorized participant age as youths—young adults (14–24 years) or older individuals (>24 years). The majority of youths were street involved: they reported having “ever taken off or run away from home for 3 or more consecutive nights.” Dividing the study population into youths and adults reflected our group’s research interest in understanding disease transmission among individuals aged 14 to 24 years.¹⁸ We coded gender as male, female, or transgender and sexual orientation as heterosexual or not heterosexual. We categorized ethnicity as White, First Nation, Métis, or other—unsure. First Nation is a Canadian term to indicate people of aboriginal descent. Participants described themselves as Métis (individuals of mixed European and First Nation ancestry) with sufficient frequency to merit a separate category. Other consisted of a small number of individuals who self-reported as Asian, Black, or another designation. We coded education as graduated grade 12 or currently in school versus dropped out. We differentiated main income from part- or full-time employment and monetary support from friends, family, government, or various types of illegal income. We coded housing as stable (1 reported residence in the past 6 months) versus unstable (>1 residence).

Individual behavioral variables. For each substance other than alcohol, we asked participants whether they had ever used it. We assessed frequency of alcohol consumption with the question, “In the last 6 months, how often did you have a drink?” (the questionnaire defined “drink” as an alcoholic beverage). This measure therefore referred to recent activity. At the

point of data analysis, because 99% of study participants had reported ever using alcohol, our measure of recent use ensured variation in the distribution of responses. We coded alcohol consumption as low (not at all or once in a while, not every week) or high (regularly, 1–2×/week; regularly, ≥3×/week; or every day).

We assessed noninjection crack use and solvent use by affirmative answers to questions related to ever having smoked crack or sniffed any solvents. We asked about smoked crack because of its frequent use in Winnipeg and other areas and because local public health campaigns were distributing safer-crack kits. We included the solvent question because of our earlier finding that solvent use is disproportionately associated with infection by bloodborne pathogens.¹⁹ We captured injection drug use as an affirmative response to a question related to ever having injected any nonprescription drug. In contrast with our measures for noninjection use, we used a broad categorization of injecting as an indicator of a very different form of drug use that has a direct, proximate link to infection risk.

We measured mental health status by a positive response to the question, “Have you ever been given a diagnosis of a mental health condition by a doctor, psychiatrist or psychologist?” We coded early substance use initiation as a report of initiating any use of alcohol, solvents, crack, or any other injection or noninjection substance prior to or at the age of 12 years.

Network variables. Network-level measures of substance use captured whether an individual used substances in isolation or socially. These measures were meant to correspond to our individual variables. In answers to 4 separate questions, participants reported whether they smoked crack, whether they regularly drank alcohol or used other noninjection drugs with a network member, and whether an injection drug user was a member of their network (the questionnaire did not have a specific question on solvent use with network members). We dichotomized this data to reflect whether 1 or more network members were present for the use of a given substance in a participant’s egocentric network.

Two additional questions provided an indication of sexual behaviors at the network level. Study participants identified which network

members were current or past sexual partners. A follow-up question then asked whether study participants believed that person was also having sexual intercourse with other individuals during the time of their sexual relationship (“During the time you were having a sexual relationship with [network member], do you think they were having sex with other partners?”). The former question measured a type of social connection within a network as opposed to actual positive or negative risk. The latter, external sexual concurrency, measured a risk that encapsulated aspects of a potential power imbalance within a sexual relationship, similar to our earlier work with power imbalance related to syringe sharing.²⁰

Infection status variables. We offered participants the option of providing a serum specimen for HIV and HCV testing. We coded infection status as negative or positive. In Winnipeg, transmission of HIV involves both bloodborne and sexual transmission, and HCV is primarily associated with bloodborne transmission²¹; we therefore included these 2 pathogens as markers of distinct types of risk behaviors. Approximately 10% of study participants refused testing, and we included refusals as a separate category for each pathogen. We used the ADVIA Centaur HIV 1/0/2 Assay (Siemens, Oakville, Ontario, Canada) for HIV testing and Abbott Anti-HCV (Abbott Laboratories, North Chicago, IL) for HCV testing. Cadham Provincial Laboratory (Winnipeg) conducted all testing.

Data Analysis

We used LCA to establish a baseline model of risk profiles encompassing 11 of our individual and network behavior measures. We chose the number of classes according to (1) risk profiles that best fit the structure of the data (i.e., goodness-of-fit indices) and (2) profiles that represented theoretically and practically meaningful patterns.^{7,22–24} Fit indices were the likelihood ratio test statistic G^2 and 3 information criteria: AIC, the Akaike information criterion; CAIC, the consistent AIC; and the Bayesian information criterion. We addressed model identification by using 1000 random starting values. For the LCA, we treated any study participants who refused to answer a question or were unsure of their response as missing in the data. Fewer than 2% of data were missing overall across all of the variables

used for LCA; we assumed data to be missing at random and accounted for them with a full-information maximum likelihood procedure.²⁵

Following identification of the latent classes, we used LCA with covariates to identify sociodemographic and infection status variables associated with class membership. We analyzed these variables individually and subsequently ran significant variables simultaneously in a multivariate model. We conducted LCA and LCA with covariates with SAS PROC LCA version 1.2.7.²⁶

RESULTS

Participants ranged in age from 14 to 78 years (median = 36 years; SD = 14.85 years); 20% reported their age as 14 to 24 years. Approximately half (54%; n = 317) were male; a majority (84%; n = 504) identified as heterosexual; and approximately half (54%; n = 322) identified as First Nation, followed by White (22.3%; n = 134), Métis (19%; n = 115), and other (n = 29; 5%). For participants with test results, 9% (48/527) were positive for HIV and 33% (169/518) for HCV. Mean egocentric network size was 6.1.

We compared models with 2 to 6 latent classes (Table 1). AIC indicated the more complex 5- or 6-class models; Bayesian information criterion and CAIC indicated best fit for a 4-class model. We chose the 4-class model according to the criteria of favoring model parsimony and having meaningful risk profiles. For comparative purposes, we also briefly described the 5-class model.

Four- and 5-Class Models

Table 2 shows the 4 latent classes relative to the indicator variables. The solitary class (21% of total respondents) reported a high-probability response pattern to individual substance use of crack, solvents, and injection drugs, but indicated low probabilities of using these substances with network members (as well as a low probability of having a sexual partner). A majority of the solitary class also reported having been diagnosed with a mental health condition.

Similarly to the solitary class, the social-all substances class (31% of participants) showed a response pattern that reflected high probabilities of a mental health diagnosis and individual substance use across all substances

TABLE 1—Goodness-of-Fit Indices Comparing Class Models of Risk Behavior Patterns: Social Network Study III, Winnipeg, Manitoba, Canada, 2009

Class	G ² (df)	AIC	BIC	CAIC
2	1434.79 (2024)	1480.79	1581.91	1604.91
3	1244.23 (2012)	1314.23	1468.12	1503.12
4	1112.62 (2000)	1206.62	1413.27	1460.27
5	1039.94 (1988)	1157.94	1417.35	1476.35
6	989.89 (1976)	1131.89	1444.07	1515.07

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; CAIC = consistent AIC.

(frequent alcohol use; crack, solvent, and injection drug use). These respondents differed from the solitary class in having high probabilities of using substances with network members, having a network member who was a sexual partner, and reporting that this partner had sexual intercourse with other partners (i.e., external sexual concurrency).

The social–noninjection class (24% of participants) also used substances with network members. However, these users showed a low probability ($\rho = 0.07$) of reporting individual frequent alcohol consumption and a relatively low probability for network alcohol consumption ($\rho = 0.42$). Both social classes differed

from the solitary and low-risk classes in their higher likelihood of having sexual partners whom they perceived as engaging in sexual intercourse with others.

Finally, a low-risk class (24% of respondents) showed an overall response pattern that reflected low probabilities across most items. These included self-report of having a serious mental health diagnosis, individual substance use (alcohol, crack, solvents, injection drugs), and substance use with network members. For this class, only network use of alcohol and having a network member who was also a sexual partner had response probabilities above 0.50.

TABLE 2—Prevalence and Response Probabilities for a Latent Class Model of Mental Health Diagnosis and Individual And Network Substance Use And Sexual Behaviors: Social Network Study III, Winnipeg, Manitoba, Canada, 2009

Variable	Latent Class			
	Low Risk (24%), ρ	Solitary (21%), ρ	Social-Noninjection ^a (24%), ρ	Social-All Substances ^a (31%), ρ
Individual level				
Mental health diagnosis	0.33	0.67	0.72	0.72
Frequent alcohol use	0.38	0.46	0.07	0.86
Crack use	0.31	0.91	0.93	0.98
Injection drug use	0.04	0.67	0.69	0.62
Solvent use	0.14	0.50	0.55	0.53
Network level				
Alcohol use	0.60	0.47	0.42	0.99
Crack use	0.01	0.36	0.46	0.63
Injection drug use	0.17	0.38	0.78	0.58
Other drug use	0.50	0.48	0.57	0.84
Presence of sexual partner	0.60	0.09	0.99	0.99
External sexual concurrency	0.19	0.00	0.70	0.77

Note. The probability of endorsing an item with a yes response is shown. The sample size was n = 600.

^aThe class names of social–noninjection and social–all substances were chosen after inclusion of HCV status as a covariate.

The only notable difference between the 4- and 5-class models was the apparent division of the low-risk participants into 2 classes. In the 5-class model, 1 of these classes (14% of participants) showed an item response probability above 0.5 only for the presence of a sexual partner; the second class (11% of participants) showed probabilities above 0.5 for frequent alcohol use, network use of alcohol and other drugs, and the presence of a sexual partner. The 3 remaining classes in the 5-class model resembled the solitary class and the 2 social classes from the 4-class model (probabilities for all indicator variables varied by no more than ± 0.04 between the 2 models for these 3 classes). In light of our focus on the differentiation of solitary versus social network use of substances and sexual risk, we favored the 4-class latent model.

Latent Class Analysis With Covariate Analysis

To further describe and validate the 4-class model, we used sociodemographic and infection status variables in LCA with covariate analyses. Initially, we entered all covariates individually in the model. Of the 8 sociodemographic variables, gender, ethnicity, income, and sexual orientation did not predict class membership, but age, education, housing, and substance use before or at the age of 12 years did. Of the 2 infection status variables, both HIV and HCV predicted class membership (data not shown). For the latter variable, a notable change occurred in the covariate analysis: probabilities of individual injection drug and solvent use decreased for the social–noninjection class (ρ decreased from 0.69 to 0.15; solvent use ρ decreased from 0.55 to 0.23). In addition, and consistent with this change, the network injection drug use probability also decreased from the baseline LCA model (network injection drug use ρ decreased from 0.78 to 0.46). The response pattern to individual and network injection drug use therefore distinguished the social–noninjection class from the social–all substances class. Indicator variable probabilities were not fixed in the covariate analyses, and changes to the baseline model could occur²⁷; in our analysis, HCV was the only covariate to have this effect.

We simultaneously entered into the model the sociodemographic and infection status

variables that predicted latent class individually. Relative to the low-risk class, 3 of the 4 sociodemographic variables significantly predicted latent class ($P < .05$): being older than 24 years and having an unstable housing situation predicted membership in the solitary and social classes, engaging in substance use before or at the age of 12 years predicted membership in the social–all substances class, and education no longer significantly predicted class membership (Table 3). For the infection status variables, relative to the low-risk class, HIV no longer predicted class membership, and HCV showed an association with membership in the solitary and social–all substances classes (Table 3).

DISCUSSION

The most notable finding of our LCA was the differentiation of classes that resulted from inclusion of social network variables. When we examined individual risk behaviors (Table 2), the solitary and social–all substances classes were similar (both with and without HCV as a covariate). Both of these classes had similar probabilities for individual use of solvents, crack, and injection drugs as well as a mental health diagnosis. Their differentiation arose from network variables, which revealed the social and nonsocial use of substances, as well as differences in network sexual behaviors.

These findings generate several research questions relevant to understanding STBBI transmission dynamics and intervention

development. For the solitary class, it is conceivable that a lesser likelihood of using substances with network members could have both positive and negative implications. Positive aspects of substance use in isolation relate to fewer opportunities for transmission of bloodborne pathogens between infected and noninfected users (the near absence of sexual partners in this group would also lower the probability of infection via a sexual transmission route). Conversely, negative effects would ensue if less frequent contact with other substance users also meant less exposure to harm reduction messages that may spread by word of mouth between users. Additional research is necessary to better understand these contrasts and how they affect actual risk.

The identification of the social classes raises questions regarding whether the social interaction is mutual on the part of 2 or more individuals or whether peer pressure or power imbalance leads to social coercion to use substances with others. Understanding the social use of substances is important, because individual-based approaches to substance abuse treatment would be expected to have less impact in situations where ongoing social interaction with other users could continue to reexpose an individual to those substances.

Although not directly related to, or affecting, our main finding of solitary versus social risk classes, inclusion of HCV as a covariate altered some indicator variable probabilities. This alteration resulted in differentiation of the 2 social classes by their patterns of substance use.

TABLE 3—Odds Ratios for Latent Class Analysis With Covariate Analysis of Risk Behavior Patterns: Social Network Study III, Winnipeg, Manitoba, Canada, 2009

Variable	Latent Class			
	Solitary, OR (95% CI)	Social-Noninjection, OR (95% CI)	Social-All Substances, OR (95% CI)	Low Risk ^a (Ref)
HCV	17.8 (6.5, 48.5)	0.5 (0.1, 2.1)	27.3 (10.4, 71.6)	1.0
HIV	1.1 (0.3, 3.3)	0.7 (0.2, 2.5)	0.9 (0.3, 2.9)	1.0
Age (> 24 y)	18.2 (5.3, 62.5)	4.3 (2.2, 8.1)	5.7 (2.7, 11.7)	1.0
Housing (> 1 residence in past 6 mo)	2.7 (1.3, 5.3)	3.0 (1.7, 5.5)	3.8 (2.0, 7.0)	1.0
Substance use initiation age (aged ≤ 12 y)	1.6 (0.8, 3.0)	1.3 (0.7, 2.3)	3.3 (1.8, 6.0)	1.0
Education	1.7 (0.8, 3.4)	0.8 (0.5, 1.4)	1.4 (0.8, 2.6)	1.0

Note. CI = confidence interval; OR = odds ratio. The sample size was $n = 592$; individuals with indeterminate HCV results were dropped from the analysis.

^aSpecified as the reference class for the multinomial logistic regression.

In the baseline model, alcohol use differed between the 2 social classes; after inclusion of HCV, these 2 classes were differentiated by solvent use and both individual and network use of injection drugs. As a covariate, HCV positivity predicted membership in the social-all substances and solitary classes, consistent with the presence of injection drug and solvent use in both of these classes. This association was consistent with our earlier findings in Winnipeg that HCV is associated with specific types of injection drug use, in particular with solvents.^{19,21} Overall, these results suggest that incorporation of substance use patterns and associated risk behaviors in LCA at both the individual and network levels (which the final outcome measure of infection would be reflecting as a proxy indicator) would open up numerous avenues of research that could better refine our understanding of STBBI risk.

Limitations

Our LCA was a secondary use of the data available, which provided less than perfect agreement between the individual and social network variables. We obtained our study sample through respondent-driven sampling, and despite its advantages, initial claims that the resultant samples were representative of the population in question may not be accurate.^{28–32} Therefore, the findings may not generalize to the larger population from which the sample was drawn. Furthermore, as noted by others,⁶ the sampling techniques typically used to access populations vulnerable to STBBIs, including respondent-driven sampling, result in participants not being independent, which violates an assumption of LCA.

As with all cross-sectional studies, causal relationships could not be ascertained. In addition, detailed recall of interactions with network members may be less accurate than participants' recall of their own individual actions. Our general use of ever use with other network members was meant to simplify recall; however, using other measures of behaviors with a risk network member would be warranted. Finally, the study findings may not reflect the patterns that would be seen in other areas, especially in situations where demographic variables may differ greatly from those found in our geographic area.

Conclusions

A key strength of our study was the incorporation of social network variables. These variables differentiated latent classes whose network use of substances and network-related sexual behaviors differed; these social contextual differences contributed to a better understanding of the nexus of risk related to STBBIs. We further highlighted the numerous research questions that emerged from this approach regarding both better understanding of the behavioral context of co-occurring substance abuse, sexual risk, and mental health issues and the potential implications for treatment services. Further research is warranted to continue to expand our understanding of the social context of STBBI disease risk and transmission. ■

About the Authors

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Contributors

S. Hopfer and J. L. Wylie conceptualized the latent class analysis study design and contributed equally to writing the article. X. Tan advised on the statistical methods. S. Hopfer led the data analysis. All authors interpreted the results.

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Human Participant Protection

The study received ethics approval from the health research ethics board of the University of Manitoba and the Winnipeg Regional Health Authority research review committee.

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