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Factors associated with patterns of mobile technology use among persons who inject drugs

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Abstract

Background—New and innovative methods of delivering interventions are needed to further reduce risky behaviors and increase overall health among persons who inject drugs (PWID). Mobile health (mHealth) interventions have potential for reaching PWID; however, little is known about mobile technology use (MTU) in this population. In this study, the authors identify patterns of MTU and identified factors associated with MTU among a cohort of PWID.

Methods—Data were collected through a longitudinal cohort study examining drug use, risk behaviors, and health status among PWID in San Diego, California. Latent class analysis (LCA) was used to define patterns of MTU (i.e., making voice calls, text messaging, and mobile Internet access). Multinomial logistic regression was then used to identify demographic characteristics, risk behaviors, and health indicators associated with mobile technology use class.

Results—In LCA, a 4-class solution fit the data best. Class 1 was defined by low MTU (22%, n = 100); class 2, by PWID who accessed the Internet using a mobile device but did not use voice or text messaging (20%, n = 95); class 3, by primarily voice, text, and connected Internet use (17%, n = 91); and class 4, by high MTU (41%, n = 175). Compared with low MTU, high MTU class members were more likely to be younger, have higher socioeconomic status, sell drugs, and inject methamphetamine daily.

Conclusion—The majority of PWID in San Diego use mobile technology for voice, text, and/or Internet access, indicating that rapid uptake of mHealth interventions may be possible in this

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population. However, low ownership and use of mobile technology among older and/or homeless individuals will need to be considered when implementing mHealth interventions among PWID.

Keywords

Latent class analysis; methamphetamine; mHealth; persons who inject drugs; risk behaviors; substance use

Introduction

Injection drug use has been widely associated with risky behaviors such as sharing injection equipment (e.g., cookers, cotton, and water) and drug paraphernalia (e.g., syringes and needles).[1] These risk behaviors contribute to an increased risk for infection with blood-borne pathogens such as human immunodeficiency virus (HIV) and hepatitis C virus (HCV) among persons who inject drugs (PWID).[1] In addition to practicing risky behaviors, PWID have low access to—and utilization of—health care services[2] and are at increased risk for loss to follow-up when being treated for disease.[3] Novel approaches to intervention delivery are needed to increase prevention effectiveness among PWID.

mHealth is defined as the use of mobile and wireless devices to improve health outcomes, health care services, and health research.[4] mHealth strategies allow researchers to build motivational, educational, and disease management interventions specifically tailored to the target population.[5] These methods have been used among various substance using populations.[6–9] For example, remote ecological momentary assessment (EMA) has been used to identify mood associations with drug cravings among polydrug users enrolled in methadone maintenance.[6] Also, text messaging–based interventions have been used to increase HIV antiretroviral therapy (ART) adherence among noninjection substance users.[8,9] mHealth-based strategies may also have the potential to deliver harm reduction interventions among PWID.

To determine how mHealth interventions can be used effectively among PWID, it is important to understand how this group commonly uses mobile technology and identify subgroups of PWID who may be reachable via mHealth intervention strategies. Data regarding mobile technology use (MTU) among other high-risk populations suggests that there is some access to mobile technology among high-risk individuals. A study of noninjection substance users enrolled in drug treatment in Baltimore reported that 91% of participants had access to a cell phone and 79% used text messaging.[10] Another study assessing technology use among homeless youth in Los Angeles—55% of whom used an illicit substance in the past 30 days—found that 62% owned a cell phone.[11] Among current smokers living with HIV, 73% of respondents owned and used a cell phone, 39% reported text messaging, 48% used the Internet, and 31% accessed e-mail (medium of Internet access was not specified).[12]

There are no published data regarding MTU specific to PWID in the United States. Thus, this study aimed to (1) categorize PWID based on their mobile technology use; and (2) identify sociodemographic, behavioral, and health-related factors associated with each category of MTU among PWID living in San Diego. The findings of this study will inform the development and implementation of mHealth research and interventions targeting PWID.

Methods

Study population and recruitment

Data for this analysis came from the "Study to assess TB, HIV and Hepatitis C Risk," which is an ongoing longitudinal cohort study of PWIDs (hereafter the STAHR-II study) in San Diego County, California. The STAHR-II study is a prospective cohort study that enrolled participants between June 2012 and January 2014. Details about the study design, participant eligibility, recruitment and enrollment procedures, and study incentives are described elsewhere.[13,14] Consented and enrolled participants underwent behavioral assessments and serologic testing at baseline and 4 semiannual follow-up visits. All participants were offered referrals for drug treatment and other services in addition to counseling and educational materials. The Human Research Protections Program of the University of California San Diego approved all study procedures.

Study measures

Surveys were conducted using computer-assisted personal interviewing (CAPI) technology. Baseline interviews measured sociodemographic information (i.e., age, sex, race/ethnicity, educational attainment, income, housing status, country of birth, marital, and parental status), lifetime and recent substance use history (i.e., specific drugs used), syringe- and injection equipment–sharing behaviors, sex in exchange for drugs or money, selling drugs, health and/or harm reduction services use (i.e., emergency room [ER]/hospital visits, use of syringe exchange program, drug treatment), and health status (i.e., lifetime overdose and ever being diagnosed with a sexually transmitted infection [STI]). All behavioral questions referred to the 6 months prior to completing the baseline interview. MTU variables included in this analysis were lifetime/current cell phone ownership, current smartphone ownership, lifetime lost/stolen cell phone, frequency of calling/texting, Internet use [in the] past 6 months, and medium of Internet use in the past 6 months (i.e., desktop, laptop, television, game console, tablet, or cell phone Internet access).

Latent class analysis (LCA) requires that only binary variables be used as indicator variables to identify latent constructs. Thus, each MTU variable was recoded into a binary variable before running the LCA. Frequency of voice calls and text messaging were recoded from "average number of calls per day" and "average number of texts per day" to "calls daily" and "texts daily" (1 = yes, 0 = no), respectively. *Any* Internet use in the past 6 months was coded as "ever accessed the Internet in the past 6 months" (1 = yes, 0 = no). *Mobile* Internet use was recoded into a binary variable, from "how did you access the Internet most in the past 6 months" (1 = computer/laptop, 2 = television, 3 = tablet, 4 = mobile phone, 5 = game console, 6 = other) to "accessed the Internet on a cell phone or tablet, past 6 months" (1 = yes, 0 = no). *Computer*-only Internet use was recoded into a binary variable, from "how did you access the Internet most in the past 6 months" (1 = computer/laptop, 2 = television, 3 = tablet, 4 = mobile phone, 5 = game console, 6 = other) to "only accessed the Internet on a computer/laptop, past 6 months" (1 = yes, 0 = no). Internet use questions were added to the baseline survey after initial study enrollment had already begun; thus, participants who were missing data for "*ever accessed the Internet in the past 6 months*," "accessed the Internet on a cell phone or tablet past 6 months," or "only accessed the Internet on a computer/laptop past 6 months" were filled in from identical questions in the 6-month follow-up interview using next observation carried backward (NOCB). To reduce potential misclassification bias, we only included MTU variables as indicators where at least 15% of participants reported their use for inclusion in the LCA.[14]

Statistical methods

A cross-sectional data set using both baseline and 6-month follow-up data was created, and all participants who answered questions regarding MTU in the baseline *or* 6-month follow-up interview ($n = 461$) were eligible for this analysis. We approached our analysis in 2 steps. First, we used LCA to identify categories of MTU, based on patterns of voice, text, and Internet use among the cohort. We used a multistep approach for our LCA by running the indicators first and then adding the covariates/predictors in a multinomial logistic regression model after class membership had been established.[14] This method classifies participants into groups for the latent categorical variable and then treats the groups as discrete entities in subsequent logistic regression analyses. Second, we used multinomial logistic regression to identify sociodemographic characteristics, risk behaviors, and health outcomes associated with class membership. We used the following 5 binary variables as indicators in our LCA to determine MTU profiles among the cohort: (1) daily cell phone calls, (2) daily text messaging, (3) any mobile Internet use in the past 6 months, (4) any Internet use past 6 months, and (5) any connected Internet use past 6 months. We then examined models with between 2 and 5 classes.

Following LCA, we identified class membership for each subject and conducted multinomial logistic regression to identify factors associated with each class. Bivariate analyses using chi-square and Kruskal-Wallis tests were conducted first to assess the association between demographic, behavioral, or health status indicators and class membership. Factors that were statistically significant at the $P < .10$ in bivariate analyses were considered for inclusion in the multivariable analysis. We used a backward model building approach, starting with a saturated model and manually removing variables with a nonsignificant overall P value. Variables achieving significance at the $P < .05$ level and variables that produced a 10% or greater change between the crude and adjusted odds ratios (i.e., confounders) were retained in the final model. Models were checked for meaningful interactions, although none were statistically significant. Multicollinearity was assessed using variance inflation factors (VIFs). In the case of collinearity, the most important variable was retained in the model. All analyses were performed with SAS version 9.3 (SAS, Cary, NC).

Results

Of the 574 participants enrolled in STAHR-II between June 2013 and January 2014, 461 (80.3%) were eligible for this analysis. There were no statistically significant differences in sociodemographics or risk behaviors between STAHR-II participants included and excluded in this analysis (data not shown). The majority of our sample was white (52.3%) and male (74.1%), with a mean age of 43.5 years (range: 18–70; SD = 11.4). Ninety-two percent reported ever owning a cell phone; 66.2% reported currently owning a cell phone and 28.6% reported currently owning a smart phone. Of current cell phone owners, 40% had a contract plan and 39% had prepaid service. Seventy percent of participants reported ever losing a cell phone; 56% ever had one stolen. Seventy-two percent of participants reported accessing the Internet in the past 6 months, of whom 63% accessed e-mail, 42% used a social networking site, and 9% used the Internet to find sex partners; 23% of participants reported *never* using the Internet before. Additional sociodemographic, HIV risk behavior, health services utilization, and health outcome factors stratified by class membership are displayed in Table 1.

Determination of class membership

Based on the entropy values, class membership standard errors, and mean posterior probabilities, we selected a 4-class solution for the LCA.[15–20] Fit statistics for LCA models with between 1 and 5 classes are presented in Table 2. A 5-class solution was slightly better in terms of the goodness-of-fit indices for LCA (lower Akaike information criterion [AIC], Bayesian information criterion [BIC], and sample size–adjusted BIC); however, the standard errors for class membership probabilities were larger and mean posterior probabilities were lower for the 5-class solution (data not shown). Although the classes were not perfectly delineated, the 4-class solution provided categories of MTU that were more stable and intuitive among this cohort and were consistent with previously published parameters.[18,21,22] Table 3 presents the conditional probability that respondents in each class indicated daily texting on a cell phone, daily calls on a cell phone, any Internet access in the past 6 months, any mobile Internet access in the past 6 months, and only accessing the Internet on a computer in the past 6 months. Class 1 represents PWID who had a high probability of low MTU, whereas class 4 represents PWID who had a high probability of using all forms of mobile technology examined, but a low probability of using a computer only to access the Internet. Two other classes represent PWID who accessed the Internet using a mobile device but did not use voice or text messaging (class 2), and PWID who mainly used voice, text, and only accessed the Internet on a computer (class 3). Of those who predominantly use mobile Internet (class 2), 75.9% used both a cell phone *and* another medium (computer/laptop, game console, or tablet) to access the Internet in the past 6 months.

Bivariate analysis of factors associated with class membership

Results of the bivariate logistic regressions comparing the odds of being in classes 1–4 are displayed in Table 1. Sociodemographic differences by class were observed for age, educational attainment, income, homelessness, having children, and lifetime incarceration. Differences in risk behaviors between classes were observed for number of years injecting, sharing syringes, selling drugs, and injecting methamphetamine daily in the past 6 months. In terms of health-related behaviors and outcomes, differences in class membership were observed for having more than 1 emergency room visit in the past 6 months, and having ever overdosed. All P values for significant differences were less than .05.

Multivariable analysis of factors associated with class membership

Using low MTU (class 1) as the reference group, multinomial logistic regression analysis revealed that high MTU (class 4) was positively associated with having more than a high school education (adjusted odds ratio [AOR] = 5.23, 95% confidence interval [CI] = 2.46, 11.09), selling drugs for money (AOR = 3.30, 95% CI = 1.53, 7.13), injecting methamphetamine daily (AOR = 2.59, 95% CI = 1.02, 6.59), and currently owning a smart phone (AOR = 14.2, 95% CI = 6.37, 31.60), compared with low MTU (Table 4). Older age (AOR = 0.92 per year, 95% CI = 0.88, 0.95) and homelessness (AOR = 0.30, 95% CI = 0.16, 0.57) were associated with lower odds of being a high MTU class member compared with low MTU. Subjects who reported having more than a high school education (AOR = 2.66, 95% CI = 1.13, 6.30), selling drugs for money (AOR = 3.52, 95% CI = 1.51, 8.23), and injecting methamphetamine daily (AOR = 5.80, 95% CI = 2.23, 15.10) were more likely to be predominantly mobile Internet users (class 2) when compared with low MTU, whereas older participants (AOR = 0.91 per year, 95% CI = 0.88, 0.95) had decreased odds of being mobile Internet users when compared with low MTU. Lastly, compared with low MTU, predominantly voice, text, and connected Internet users (class 3) were more likely to have more than a high school education (AOR = 2.62, 95% CI = 1.25, 5.47) and inject methamphetamine daily (AOR = 3.54, 95% CI = 1.46, 8.60). Older participants (AOR = 0.95 per year, 95% CI = 0.92, 0.98) were also less likely to be predominant voice, text, and connected Internet users compared with low MTU.

Discussion

We identified 4 distinct classes of MTU among PWIDs in San Diego, California: (1) low MTU; (2) predominantly mobile Internet users; (3) predominantly voice, text, and connected Internet users; and 4) high MTU. This is the first study, to our knowledge, that classified PWID by MTU behaviors and identified factors associated with these classes. Compared with low MTU class members, participants who were younger, stably housed, have higher education, currently own a smart phone, and sell drugs and/or inject methamphetamine daily in the past 6 months were more likely to be high MTU class members. These findings provide new insights about PWID that could be used to design mHealth-based risk prevention interventions.

The US/Mexico border region is a unique setting to study drug abuse. This region is situated along a major drug trafficking route; illicit drugs such as heroin, cocaine, and methamphetamine are readily available in San Diego and Tijuana, leading to a high prevalence of drug abuse in the region.[23] San Diego has an estimated 21,000 PWID living in the county,[24] many of which have low socioeconomic status (SES). In this study, 61% of PWID consider themselves to be homeless and >90% had an average yearly income below $10,000. Also, in this analysis, most PWID in San Diego (92.4%) reported ever owning a cell phone, although current cell phone ownership was much lower at 66%, and just under a third of participants (28.6%) currently owned a smartphone. In contrast, Pew Research Center estimated that 90% of American adults owned a cell phone in 2014, and 58% owned a smartphone—among adults making less than $30,000/year, 47% owned a smartphone.[25] This disparity was not surprising given that PWID in this study were generally of low SES.

In multivariable analyses, homeless participants were more likely to be low MTU compared with high MTU, further demonstrating that low SES contributes to low access to mobile technology. Additionally, more than two thirds of participants reported ever losing a cell phone. Low-SES individuals who are actively engaged in their addiction may have access to a device, but not necessarily one that is functional. Given the low prevalence of smartphone ownership and high prevalence of lifetime cell phone loss among PWID, device coverage will need to be considered when developing smartphone-based interventions among PWID.

Consistent with recent data, owning a smartphone significantly increased the odds of being in the high MTU category.[25] In 2014, Pew reported 81% of cell phone owners in the United States used their device to send or receive text messages; in the case of smartphone ownership, 60% used their device to access the Internet, and 52% to send or receive e-mail.[25] Also consistent with recent data, mobile technology classes were associated with differences in age and education.[25] Higher educational attainment and younger age increased the odds of higher MTU across all classes compared with low MTU. These trends among PWID in San Diego are consistent with recent data among other high-risk populations in the United States (e.g., homeless youth, non-injecting substance users, smokers living with HIV) that demonstrate that younger age and higher education are associated with increased cell phone ownership, cell phone use, and Internet and e-mail use.[10–12,26]

Injecting methamphetamine daily was associated with increased odds of higher MTU across all classes compared with low MTU class members. In contrast, daily heroin injection was not associated with increased MTU. Both drugs are highly addictive, but in the case of heroin, once a person becomes an addict, seeking and using their drug of choice to avoid withdrawal sickness becomes their highest priority.[27] Individuals addicted to heroin may do anything in their power to obtain drugs and avoid withdrawal, including spending available resources on drugs rather than maintaining a mobile device. In contrast, daily methamphetamine users may be higher functioning due to the stimulating effects of methamphetamine[28] and more able to obtain and maintain the resources to access a cell phone or use mobile technology than daily heroin users in this study.

Selling drugs in the past 6 months was associated with increased odds of high MTU, and being a predominant mobile Internet user. Access to some form of mobile technology may be a high priority for individuals who sell drugs, as a communication technology equals access to their customers. As mobile phones have become nearly ubiquitous among all socioeconomic and demographic groups in the United States, individuals who sell drugs are now using smartphones and the Internet to connect with customers and suppliers.[29,30] Mobile Internet applications allow for nearly instantaneously connection and often make communication discreet and efficient. However, “smart” technology may be a privacy and/or legal risk for individuals who sell drugs due to easy traceability of Global Positioning System (GPS)-enabled devices.[31] In this study, 39% of current cell phone owners reported using a prepaid cell phone plan that permits the user to obtain a new phone number each time they pay for service. Although PWID who sell drugs utilize mobile technology, and thus may be reachable via mHealth interventions, confidentially may be of concern to this subgroup who engage in illicit behaviors.

These findings must be interpreted with some limitations. Cross-sectional data from the baseline interview of the STAHR-II study was utilized for this analysis. Thus, we are unable to establish directionality between class membership and risk behaviors or health status. Since MTU class membership—particularly in the rapidly expanding technology market—and risk behaviors and health status are likely to change over time, future analyses are needed using longitudinal data to model whether class membership is stable and whether/how transitions between classes impact risk behaviors and health status over time. As the MTU questions were added to the study part way through enrollment, 224 participants were not asked these questions at baseline. To minimize missing data, we used responses for these questions from 120 participants who returned for their 6-month interviews. This could have resulted in some misclassification; however, the study was not designed to influence cell phone ownership, so any misclassification would likely be nondifferential with respect to our study measures and bias our data in the direction of null findings. Further, our reliance on using recall-based survey methods may introduce bias into the data. A short recall period (6 months) was used to minimize problems with recall. To minimize socially desirable responses, interviews were conducted in private settings with trained interviewers. Patterns identified in this paper may not be generalizable to PWID outside of the San Diego border region. Also, due to the convenience sampling used to recruit study participants for STAHR-II, these data might not be generalizable to all PWID in San Diego. Finally, although this analysis identified groups of PWID who are more likely to use mobile technology, more research is needed to understand the contextual issues surrounding MTU in this population. For example, data regarding the permanency of Internet and/or cell phone numbers and carriers, types of data plans used, willingness to download an mHealth application or visit an mHealth Web site, and comfort level in downloading and/or using mHealth applications will be important factors for researchers to consider when designing future mHealth interventions for PWID.

Conclusion

Overall, we found that the majority of PWID in San Diego currently own a cell phone; however, smartphone device ownership was much lower, with less than a third of participants owning a smartphone at the time of this study. Our findings that younger and more educated PWID in San Diego were familiar with the technology used for mobile voice, texting, and Internet access suggest that uptake of mHealth interventions may be successful in this population. Results also suggest that mHealth-based approaches may help interventionists reach a high-risk subgroup of PWID who are highly dependent on methamphetamine and may be hard to reach using traditional intervention approaches. However, device coverage should be considered when implementing mHealth interventions in this population, as lower-SES PWID may not benefit from such interventions unless they are provided with devices.

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References

[1]. Strathdee SA, Hallett TB, Bobrova N, et al. HIV and risk environment for injecting drug users: the past, present, and future. Lancet. 2010; 376:268–284. [PubMed: 20650523]

[2]. Drumm RD, McBride DC, Metsch L, Page JB, Dickerson K, Jones B. `The rock always comes first': drug users' accounts about using formal health care. J Psychoactive Drugs. 2003; 35:461–469. [PubMed: 14986875]

[3]. Arnsten JH, Xuan L, Mizuno Y, et al. Factors associated with anti retroviral therapy adherence and medication errors among HIV-infected injection drug users. J Acquir Immune Defic Syndr. 2007; 46(Suppl 2):S64–S71. [PubMed: 18089986]

[4]. United States Department of Health and Human Services. [Accessed April 25, 2014] mHealth. http://www.hrsa.aquilentprojects.com/healthit/mhealth.html. Published 2010

[5]. Marsch LA, Carroll KM, Kiluk BD. Technology-based interventions for the treatment and recovery management of substance use disorders: a JSAT special issue. J Subst Abuse Treat. 2014; 46:1–4. [PubMed: 24041749]

[6]. Epstein DH, Willner-Reid J, Vahabzadeh M, Mezghanni M, Lin J-L, Preston KL. Real-time electronic diary reports of cue exposure and mood in the hours before cocaine and heroin craving and use. Arch Gen Psychiatry. 2009; 66:88–94. [PubMed: 19124692]

[7]. Epstein DH, Tyburski M, Craig IM, et al. Real-time tracking of neighborhood surroundings and mood in urban drug misusers: application of a new method to study behavior in its geographical context. Drug Alcohol Depend. 2014; 134:22–29. [PubMed: 24332365]

[8]. Ingersoll K, Dillingham R, Reynolds G, et al. Development of a personalized bidirectional text messaging tool for HIV adherence assessment and intervention among substance abusers. J Subst Abuse Treat. 2014; 46:66–73. [PubMed: 24029625]

[9]. Moore DJ, Montoya JL, Blackstone K, et al. Preliminary evidence for feasibility, use, and acceptability of individualized texting for adherence building for antiretroviral adherence and substance use assessment among HIV-infected methamphetamine users. AIDS Res Treat. 2013; 2013:585143. [PubMed: 24078868]

[10]. McClure EA, Acquavita SP, Harding E, Stitzer ML. Utilization of communication technology by patients enrolled in substance abuse treatment. Drug Alcohol Depend. 2013; 129:145–150. [PubMed: 23107600]

[11]. Rice E, Lee A, Taitt S. Cell phone use among homeless youth: potential for new health interventions and research. J Urban Health. 2011; 88:1175–1182. [PubMed: 22076445]

[12]. Chander G, Stanton C, Hutton HE, et al. Are smokers with HIV using information and communication technology? Implications for behavioral interventions. AIDS Behav. 2012; 16:383–388. [PubMed: 21390537]

[13]. Robertson AM, Garfein RS, Wagner KD, et al. Evaluating the impact of Mexico's drug policy reforms on people who inject drugs in Tijuana, B. C. Mexico, and San Diego, CA, United States: a binational mixed methods research agenda. Harm Reduct J. Jan 28; 2015 50(2):205–214.

[14]. Roth AM, Armenta RA, Wagner KD, et al. Patterns of drug use, risky behavior, and health status among persons who inject drugs living in San Diego, California: a latent class analysis. Subst Use Misuse. 2015; 50:205–214. [PubMed: 25313832]

[15]. Gibson WA. Three multivariate models: factor analysis, latent structure analysis, and latent profile analysis. Psychometrika. 1959; 24:229–252.

[16]. Hagenaars, JA.; McCutcheon, AL. Applied Latent Class Analysis. Cambridge University Press; Cambridge, UK: 2002.

[17]. McCuthcheon, AL. Latent Class Analysis. Sage; Newbury Park, CA: 1987.

[18]. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct Equ Modeling. 2007; 14:556–569.

[19]. Lanza, ST.; Dziak, JJ.; Huang, L.; Wagner, A.; Collins, LM. [Accessed November 5, 2013] PROC LCA & PROC LTA users' guide (version 1.3.0). http://methodology.psu.edu. Published 2012

[20]. Lanza ST, Collins LM. A new SAS procedure for latent transition analysis: transitions in dating and sexual risk behavior. Dev Psychol. 2008; 44:446–456. [PubMed: 18331135]

[21]. Ramaswamy V, DeSarbo WS, Reibstein DJ, Robinson WT. An empirical pooling approach for estimating marketing mix elasticities with PIMS data. Market Sci. 1993; 12:103–124.

[22]. Wurpts IC, Geiser C. Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study. Front Psychol. 2014; 5:1–16. [PubMed: 24474945]

[23]. Volkmann T, Shin SS, Garfein RS, et al. Border crossing to inject drugs in Mexico among injection drug users in San Diego, California. J Immigr Minor Health. 2012; 14:281–286. [PubMed: 21442300]

[24]. Friedman SR, Tempalski B, Cooper H, et al. Estimating numbers of injecting drug users in metropolitan areas for structural analyses of community vulnerability and for assessing relative degrees of service provision for injecting drug users. J Urban Health. 2004; 81:377–400. [PubMed: 15273263]

[25]. Pew Research Center. [Accessed April 28, 2015] Mobile Technology Fact Sheet: Pew Research Center's Internet and American Life Project. http://www.pewinternet.org/fact-sheets/mobile-technology-fact-sheet/. Published 2014

[26]. Collins KM, Abramovitz D, Meacham MC, Gonzalez-Zuniga PE, Patrick K, Garfein RS. Cell phone access among persons who inject drugs in Tijuana, BC, Mexico. J Mob Technol Med. 2015; 4:13–19.

[27]. National Institute on Drug Abuse. [Accessed April 28, 2015] Heroin. http://www.drugabuse.gov/publications/drugfacts/heroin. Published 2015

[28]. National Institute on Drug Abuse. [Accessed April 28, 2015] Methamphetamine. http://www.drugabuse.gov/drugs-abuse/methamphetamine. Published 2015

[29]. Sims, C. [Accessed April 28, 2015] Schools responding to beeper, tool of today's drug dealer, by banning it. New York Times. Sep 25. 1988 http://www.nytimes.com/1988/09/25/us/schools-responding-to-beeper-tool-of-today-s-drug-dealer-by-banning-it.html

[30]. Natarajan M, Clarke RV, Johnson BD. Telephones as facilitators of drug dealing. Eur J Crim Pol Res. 1995; 3:137–153.

[31]. Zacharanda, S. [Accessed April 28, 2015] The UK's drug dealers are swapping crack for Nokia 8210s. VICE Web site. http://www.vice.com/read/the-uks-drug-dealers-love-the-nokia-8210-988. 2015

Table 1

Bivariate analysis of MTU class by sociodemographic characteristics, HIV risk behaviors, health services utilization, and health outcomes among persons who inject drugs.

Variable	All subjects (*N* = 461) *n* (%)[†]	Class 1[a] (*n* = 128) *n* (%)[§]	Class 2[b] (*n* = 58) *n* (%)[§]	Class 3[c] (*n* = 83) *n* (%)[§]	Class 4[d] (*n* = 192) *n* (%)[§]	*P* value[//]
Sociodemographic characteristics						
Gender (*N* = 455)						
Male	337 (74.1)	96 (76.8)	47 (81.0)	60 (73.2)	134 (70.5)	.358
Female	118 (25.9)	29 (23.2)	11 (19.0)	22 (26.8)	56 (29.5)	
Age, mean (SD)	43.5 (11.4)	49.9 (8.7)	39.6 (10.9)	44.7 (11.6)	39.9 (11.2)	<**.0001**
Race/Ethnicity						
White	241 (52.3)	53 (41.4)	33 (56.9)	49 (59.0)	106 (55.2)	.227
Hispanic	141 (30.6)	50 (39.1)	18 (31.0)	22 (26.5)	51 (26.6)	
Black	41 (8.9)	15 (11.7)	3 (5.2)	5 (6.0)	18 (9.4)	
Other	38 (8.2)	10 (7.8)	4 (6.9)	7 (8.4)	17 (8.9)	
Educational Attainment						
<High school	153 (33.2)	59 (46.1)	22 (37.9)	30 (36.1)	42 (21.9)	<**.0001**
High school or equivalent	136 (29.5)	45 (35.2)	16 (27.6)	23 (27.7)	52 (27.1)	
>High school	172 (37.3)	24 (18.8)	20 (34.5)	30 (36.1)	98 (57.0)	
Income						
$0–10,000	319 (69.2)	95 (74.2)	41 (70.7)	64 (77.1)	73 (38.0)	**.034**
>$10,000	142 (30.8)	33 (25.8)	17 (29.3)	19 (22.9)	119 (62.0)	
Source of Income (past 6 months) (N = 444)						
Illegal source	23 (12.5)	14 (11.1)	14 (25.0)	6 (7.7)	23 (12.5)	.065
Irregular legal source	85 (46.2)	52 (41.3)	19 (33.9)	40 (51.3)	85 (46.2)	
Regular legal source	191 (43.2)	60 (47.6)	23 (41.1)	32 (41.0)	76 (39.8)	
Homeless, past 6 months	282 (61.2)	90 (70.3)	42 (72.4)	53 (63.9)	97 (50.5)	<**.001**
Have children	261 (56.6)	91 (71.1)	29 (50.0)	44 (53.0)	97 (50.5)	**.002**
Country born						
United States	434 (91.1)	121 (94.5)	57 (98.3)	78 (94.0)	178 (92.7)	.380
Mexico	11 (2.4)	5 (3.9)	0 (0)	1 (1.2)	5 (2.6)	
Other	16 (3.5)	2 (1.6)	1 (1.7)	5 (4.8)	9 (4.7)	
Ever incarcerated	420 (91.1)	125 (97.7)	55 (94.8)	73 (87.9)	167 (87.0)	**.005**
Married (vs. single)	408 (88.5)	114 (89.0)	51 (87.9)	79 (95.2)	164 (85.4)	.139
Currently own smartphone	132 (28.6)	11 (8.6)	2 (3.5)	7 (8.4)	112 (58.3)	<**.0001**
Drug use and sexual risk behaviors[‡]						
Mean years injecting drugs (SD)	21.1 (13.2)	27.8 (12.1)	19.1 (12.8)	21.6 (13.0)	16.9 (12.3)	<**.0001**
Shared injection paraphernalia, past 6 months	316 (68.6)	94 (73.4)	46 (79.3)	48 (57.8)	128 (66.7)	.063
Shared syringe past 6 months (*N* = 399)	167 (41.9)	41 (36.9)	17 (32.1)	38 (57.6)	71 (42.0)	**.020**
Ever exchanged sex for drugs or money (*N* = 458)	150 (32.8)	39 (31.0)	19 (32.8)	25 (30.1)	67 (35.1)	.822

Variable	All subjects (N = 461) n (%)[†]	Class 1[a] (n = 128) n (%)[§]	Class 2[b] (n = 58) n (%)[§]	Class 3[c] (n = 83) n (%)[§]	Class 4[d] (n = 192) n (%)[§]	P value[‖]
Used the Internet to look for sex partners, past 6 months	40 (9.6)	1 (1.2)	9 (15.5)	5 (6.1)	25 (13.1)	**.004**
Sold drugs for money, past 6 months	128 (27.8)	18 (14.1)	22 (37.9)	18 (21.7)	70 (36.5)	<**.0001**
Inject heroin daily (N = 450)	169 (37.6)	50 (40.0)	25 (45.5)	28 (34.2)	66 (35.1)	.450
Inject methamphetamine daily (N = 449)	72 (16.0)	10 (8.1)	16 (29.1)	18 (22.0)	28 (38.9)	**.002**
Health services utilization						
Used syringe exchange, past 6 months	160 (34.7)	39 (28.1)	20 (34.5)	31 (37.4)	73 (38.0)	.304
≥1 Hospitalization, past 6 months	87 (18.9)	28 (21.9)	12 (20.7)	12 (14.5)	35 (18.2)	.575
≥1 ER visit, past 6 months	170 (36.9)	42 (32.8)	26 (44.8)	20 (24.1)	82 (42.7)	**.011**
Lifetime drug treatment	365 (79.2)	97 (75.7)	45 (77.6)	63 (75.9)	160 (83.3)	.316
Health outcomes						
Ever diagnosed with STI (self-report)	184 (39.9)	48 (37.5)	21 (36.2)	37 (44.6)	78 (40.6)	.680
Ever overdosed on opioids	186 (40.4)	64 (50.0)	27 (46.5)	30 (36.1)	65 (33.8)	**.020**

Bold values reflect significant sociodemographic variables associated with MTU class in bivariate analysis at an alpha = .05.

[a]Class 1: Low MTU.

[b]Class 2: Predominantly mobile Internet use.

[c]Class 3: Predominantly voice, text, and connected Internet use.

[d]Class 4: High MTU.

[†]Column percentages. Totals may vary by subgroup due to missing data.

[‡]All substance use and risk/harm reduction behaviors refer to the past 6 months, unless otherwise indicated.

[§]Row percentages represent prevalence of reporting a cell phone at baseline within the groups.

[‖]P values are based on chi-square and Kruskal-Wallis tests, and demonstrate overall significance of differences between LCA classes by each variable.

Table 2

Fit statistics of the latent class models among persons who inject drugs.

No. of classes	Log likelihood	AIC	BIC	sBIC	Entropy	Bootstrap LRT *P* value[†]
1 class	−1433.9	931.72	952.39	936.52	1.00	—
2 classes	−1213.4	502.58	548.05	513.13	0.91	.001
3 classes	−1120.7	329.21	399.48	345.43	0.95	.001
4 classes	**− 1042.8**	**185.46**	**280.52**	**207.53**	**0.96**	**.001**
5 classes	−1006.85	125.58	245.45	153.41	0.95	.001

Bold values reflect the best-fit-4-Class soluation.

[†]Bootstrap LRT ran for 2000 iterations.

Table 3

Latent class marginal and conditional probabilities for MTU among persons who inject drugs.

Variable‡†	**Class 1 28% (SE = 0.02)**	**Class 2 14% (SE = 0.03)**	**Class 3 18% (SE = 0.02)**	**Class 4 41% (SE = 0.03)**
Mean posterior probabilities (SD)	98.6% (0.05)	98.4% (0.03)	99.9% (0.00)	97.3% (0.08)
Daily text messages	28.9%	1.5%	**53.0%**	**93.2%**
Daily phone calls	45.8%	6.6%	**55.5%**	**98.7%**
Any Internet access§	0.5%	**94.2%**	**99.9%**	**97.4%**
Any mobile Internet access§	0.8%	**86.0%**	0.0%	**94.8%**
Computer *only* Internet access§	0.0%	0.0%	**99.3%**	0.0%

Bold values reflect the indicator variables that best defined each class in the latent class analysis.

†All indicator variables included in the latent class analysis (LCA) were ≥15% prevalent. Variables were dichotomized (yes/no) for LCA.

‡Variables with <15% prevalence did not meet the inclusion criteria for the LCA.

§Variable assessd for past 6 months.

TABLE 4

Multivariable analysis of factors associated with MTU class membership among persons who inject drugs.

Variable	Class 2[a,b] AOR (95% CI)[†]	Class 3[a,c] AOR (95% CI)[†]	Class 4[a,d] AOR (95% CI)[†]
Education			
<High school (ref)	1.00	1.00	1.00
High school or equivalent	0.84 (0.35, 2.01)	0.94 (0.46, 1.93)	1.25 (0.60, 2.59)
>High school	**2.66 (1.13, 6.30)**	**2.62 (1.25, 5.47)**	**5.23 (2.46, 11.1)**
Age (per year)	**0.91 (0.88, 0.95)**	**0.95 (0.92, 0.98)**	**0.92 (0.89, 0.95)**
Own smartphone	0.36 (0.07, 1.78)	1.00 (0.35, 2.85)	**14.2 (6.37, 31.6)**
Homeless (vs. housed)	0.63 (0.29, 1.37)	0.56 (0.29, 1.07)	**0.30 (0.16, 0.57)**
Sold drugs for money past 6 months	**3.52 (1.51, 8.23)**	1.83 (0.82, 4.10)	**3.30 (1.53, 7.13)**
Inject methamphetamine daily past 6 months	**5.80 (2.23, 15.1)**	**3.54 (1.46, 8.60)**	**2.59 (1.02, 6.59)**

Bold values reflect significant sociodemographic variables associated with MTU class in multivariable analysis at an alpha = .05.

[a]Class 1: Low MTU (reference group).

[b]Class 2: Predominantly mobile internet use.

[c]Class 3: Predominantly voice, text and connected Internet use.

[d]Class 4: High MTU.

[†]Odd ratios are adjusted for all other variables in the model.