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Technology Use Patterns Among Patients Enrolled in Inpatient Detoxification Treatment

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Abstract

Background: Technology-based interventions offer a practical, low-cost, and scalable approach to optimize the treatment of substance use disorders (SUDs) and related comorbidities (HIV, hepatitis C infection). This study assessed technology use patterns (mobile phones, desktop computers, internet, social media) among adults enrolled in inpatient detoxification treatment.

Methods: A 49-item, quantitative and qualitative semi-structured survey assessed for demographic characteristics, technology use patterns (*ie*, mobile phone, text messaging [TM], smart phone applications, desktop computer, internet, and social media use), privacy concerns, and barriers to technology use. We used multivariate logistic regression models to assess the association between respondent demographic and clinical characteristics and their routine use of technologies.

Results: Two hundred and six participants completed the survey. Nearly all participants reported mobile phone ownership (86%). Popular mobile phone features included TM (96%), web-browsers (81%), and accessing social media (61%). There was high mobile phone (3.3 ± 2.98) and phone number (2.6 ± 2.36) turnover in the preceding 12 months. Nearly half described daily or weekly access to desktop computers (48%) and most reported internet access (67%). Increased smartphone ownership was associated with higher education status (P = 0.022) and homeless

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respondents were less likely to report mobile phone ownership (P = 0.010) compared to participants with any housing status (ie, own apartment, residing with friends, family, or in a halfway house). Internet search engines were used by some participants (39.4%, 71/180) to locate 12 step support group meetings (37%), inpatient detoxification programs (35%), short- or long-term rehabilitation programs (32%), and outpatient treatment programs (4%).

Conclusions: Technology use patterns among this hard-to-reach sample of inpatient detoxification respondents suggest high rates of mobile phone ownership, TM use, and moderate use of technology to facilitate linkage to addiction treatment services.

Keywords

mobile health; substance use disorders; technology-based interventions

Inpatient detoxification programs are highly utilized among hard-to-reach populations with substance use disorders (SUDs) (Barak et al., 2009). Transitioning inpatients to addiction outpatient specialty and primary care settings remains a major obstacle in reducing the burden of SUDs (*Naeger* et al., 2016). Barriers to successful linkage to primary care post-discharge inpatient settings include inadequate administrative support and poor coordination of care for co-occurring conditions (Raven et al., 2010). Differential linkage to primary care among vulnerable populations with SUDs, characterized by race, education, and income status, further compromise treatment access (Hansen et al., 2016). The integration of novel health information technologies for populations with SUDs may optimize follow-up to primary care and adoption of effective medication-assisted treatments (naltrexone, buprenorphine).

Broader use of technology-based interventions among populations with SUDs, including smartphone applications, text messaging, and web-based interventions, have demonstrated improved rates of retention and abstinence in addiction treatment (Marsch, 2011; Newman et al., 2011; Acosta et al., 2012; Whittaker et al., 2012; Campbell et al., 2014; Gustafson et al., 2014). Recent implementation of an evidence-based mHealth intervention in primary care has demonstrated significant reductions in risky drinking days, illicit substance use, hospitalizations, and improved quality of life (Quanbeck et al., 2018). Effective mHealth interventions typically consist of interactive modules and supportive messages based on effective behavior change approaches, peer or counselor support, forums, medication and appointment reminders, and linkages to self-help groups and specialty care (Whittaker et al., 2012; Gustafson et al., 2014; Quanbeck et al., 2018).

Mobile phone-based health interventions (mHealth) have gained particular attention due to their affordability, accessibility, and effectiveness in reducing alcohol use and smoking (Whittaker et al., 2012; McClure et al., 2013; Union, 2013; Gustafson et al., 2014; Tofighi et al., 2015). Findings among lower-income, uninsured, and non-Caucasian participants receiving treatment for SUDs in primary care describe high rates of mobile phone and internet use, and interest in adopting technology-based interventions to enhance recovery (McClure et al., 2013; Tofighi et al., 2015; Tofighi et al., 2016a,b). However, the actual reach for mobile phone, computer, and internet use among inpatient detoxification patients is largely unknown. Furthermore, there is limited data characterizing preferences for adopting technology-based interventions to enhance addiction and medical outcomes among inpatients following discharge.

We explored demographic and clinical characteristics associated with technology use patterns among individuals admitted for opioid and/or alcohol inpatient detoxification program in a safety-net tertiary referral center in New York City. These findings are uniquely positioned to inform how health systems may integrate technology-based interventions among inpatient populations with SUD without exacerbating health disparities among socioeconomically disadvantaged patients.

METHODS

Participants and Recruitment

Patients enrolled in an inpatient detoxification program at Bellevue Hospital Center, a safety-net tertiary referral center in the New York City Health & Hospitals network, were approached for study participation. The program serves a primarily uninsured and Medicaid-insured adult population with alcohol and/or opioid use disorder. Convenience sampling was used to reach a quasi-representative sample of eligible participants (N = 206). On at least 2 afternoons per week from February through August 2015, research assistants invited individuals to participate in a 20- to 30-minute survey. Participants received a transportation voucher at the time of discharge for their participation in the survey. Eligibility criteria included adults 18 years and older with alcohol and/or opioid use disorder. Participants were informed that all data collected from the electronic health records and from the survey responses would be kept confidential and would not alter their routine care. The New York University School of Medicine Institutional Review Board And Bellevue Hospital Research Administration approved the study protocol.

Survey Instrument

The 49-item questionnaire required 20 to 30 minutes to complete and was administered by trained study staff and the primary investigator via paper surveys in a private office space. The questionnaire was piloted in 10 participants and modified following feedback from participants and study staff. The survey incorporated open-ended items, binomial ‘‘Yes/No’’ questions, 5-point Likert scales, and multiple-choice answers. The survey was not validated before administration; however, items were incorporated from 2 prior studies conducted by the study team in Bellevue Hospital’s office-based buprenorphine program (Tofighi et al., 2015; Tofighi et al., 2016a,b), the Pew Research Center’s Internet, Science, and Technology questionnaire (Fox and Fallows, 2014), and from relevant concepts elicited after a review of the literature (Newman et al., 2011; McClure et al., 2013; Tofighi et al., 2015; Tofighi et al., 2017).

The questionnaire was separated into the following domains: (1) demographic characteristics (10 items); (2) clinical characteristics retrieved from the electronic medical records (13 items); (3) utilization of medical resources (emergency room, inpatient detoxification, and primary care usage at Bellevue and any other location in the past year); (4) mobile phone use patterns (7 items); (5) text message usage (5 items), comfort level sending or receiving texts, preference for telephone versus text messaging contact, payment plan for text messages, and privacy concerns regarding text communication; (6) computer, internet, and social media use, including preferred location of use (own home, library, work, friend/family's house), frequency of use, and commonly utilized websites (3 items); and (7) technology use patterns to facilitate recovery or harmful substance use (7 items).

The first author (BT) ensured the methodological rigor of the interviews by reviewing a semi-structured interview guide with study staff which addressed the core survey domains while allowing flexibility to probe and follow emergent pertaining to relevant participant experiences, clinical priorities, and perceived barriers/facilitators to technology use. In addition, the first author observed study staff during at least 10 interviews and conducted weekly or bi-monthly debriefings with the study team to address any emerging issues.

Demographic characteristics included (a) age; (b) gender; (c) race/ethnicity; (d) current housing status; (e) homelessness in the preceding 12 months (yes/no); (f) number of locations the participant had resided in the last 12 months; (g) employment and means of financial support; (h) recent incarceration in the prior year (yes/no); (i) health insurance; and (j) education. Clinical characteristics consisted of (a) substance(s) of use (heroin, alcohol, crack/ cocaine, cocaine, benzodiazepine, cannabis, nicotine) and age of first use for each substance; (b) HIVand/or hepatitis C (HCV) status, and if tested positive, history of receiving or currently being prescribed treatment; (c) medical history (eg, hypertension, diabetes, asthma); and (d) psychiatric history (eg, depression, bipolar disorder, anxiety disorder). Primary care visits were defined as any encounter for the purpose of addressing physical health complaints in a non-emergency department or inpatient setting during the preceding 12 months.

Mobile phone use patterns included (a) type of phone ownership (eg, smartphone, basic cellphone, landline); (b) number of phones and phone numbers owned in the past year; (c) reasons for owning more than 1 phone or phone number in the last year (eg, stolen, cost, lost, hardware damage); (d) frequency of mobile phone service disruption in the past year (eg, loss of battery power, loss of network service, phone sharing); (e) commonly accessed mobile phone features (eg, text messaging, video, camera, e-mail, social media, smartphone applications, games); and (f) access to their phone in a manner that affected their privacy (yes/no).

The last domain incorporated open-ended items to assess for mobile phone (text messaging, smartphone application, internet search tools) and computer use to access clinical services for their recovery or general health needs as well as procuring illicit substances. If participants accessed web-based resources (eg, internet search engines, online forums, social media) to elicit information for their recovery, they were asked about the ease of use, perceived usefulness, and intention to use the available information to access treatment based on themes related to the Technology Acceptance Model (TAM) (Naeger et al., 2016). TAM provides a theoretically based approach to evaluate patient feedback pertaining to specific technologies (Venkatesh and Davis, 2000). Based on prior case reports suggesting the spread of internet-based drug markets using online forums (Bluelight, Craigslist) and social media (Instagram, Facebook), we explored whether respondents used the internet in a manner that ‘‘worsened your substance use?’’ (Tofighi et al., 2016a,b).

Data Collection and Analysis

All responses were collected by study staff in writing and data was then entered into REDCap data management software (Harris et al., 2009). The primary investigator compared the paper questionnaire responses with the collected data to correct any potential discrepancies. We utilized descriptive statistics (counts, proportions) to evaluate demographic, clinical, and technology use characteristics. Summarization of coding categories was performed across interviewee types to yield a rich descriptive analysis. Coding of the survey responses was performed by the first author and study staff using a coding guide developed by the first author. Intercoder agreement methods were performed; however, few discrepancies emerged due to the limited size and simplicity in the content being analyzed. Qualitative analysis of respondent internet search patterns pertaining to clinical services addressing addiction treatment and/or general health needs and accessing illicit substances was performed via a line-by-line review of all yielded data clusters that were labeled into brief headings of codes and then coding categories using an a priori coding scheme pertaining to each domain.

RESULTS

Demographic and Clinical Characteristics

The study sample’s demographic and clinical characteristics are similar to prior studies conducted in Bellevue Hospital (Raven et al., 2010; Tofighi et al., 2015; Lee et al., 2017) respondents were mostly male (91%), non-Caucasian (67%), unemployed or dependent on public assistance (51%), reliant on Medicaid (62%), with a mean age of 44 years (Table 1). Importantly, nearly half of the survey participants were homeless (45%) compared to only 14% of respondents in the office-based buprenorphine program. Nearly half of the respondents were admitted for alcohol detoxification (47%), and 22% of participants were admitted for both alcohol and heroin detoxification (Table 2). Approximately 4% (n = 8) reported being HIV positive and 5 of the 8 participants were adherent to antiretroviral therapy and scheduled visits with their HIV provider. Among participants positive for HCV (18%), 1 participant had received antiretroviral therapy. An additional 12% of respondents were unsure of their HCV status.

Technology Use Patterns

More participants reported smartphone ownership (66%) compared to basic cellphones (20%). Popular smart-phone applications included entertainment (eg, music, video) (46%), games (35%), and social media (25%). Respondents had on average 3.3 mobile phones (range, 0–20) and 2.6 phone numbers (range, 0–20) in the preceding 12 months. Frequent turnover of mobile phones and phone numbers was attributed to misplacing and losing phones (63%), having their phone(s) stolen (27%), and hardware damage (21%). Approximately 18% of participants reported having their phones accessed in a manner that invaded their privacy by friends, family, or strangers. Half (51%) voiced concern pertaining to the privacy of their text messaging communication (Table 3). Few reported utilization of landline phones (3%).

Table 4 displays participants' computer and internet use patterns. More than half reported daily or weekly computer use (54%) and were most frequently utilized at their own home (37%) or at the library (33%). Other locations of desktop computer access included work or school (8%), and addiction treatment programs or primary care clinics (3%). The most commonly utilized websites included social media (69%), online forums or chatrooms (53%), and internet search engines (32%).

In the multivariable model, which included all variables statistically significant at the bivariate level, only race (eg, Black, Other) ($P = 0.037$) and homelessness ($P = 0.01$) remained significantly associated with reduced mobile phone ownership at the time of the survey. However, smartphone ownership was significantly associated with higher education (ie, high school graduate) ($P = 0.022$) and internet access was significantly associated with younger age ($P = 0.035$) (Table 5).

Health Information Search Patterns

The last domain elicited participants' use of mobile phones and desktop computers to query for health services in response to their substance use or general health needs. Respondents utilized internet search engines (Google, Yahoo) (35%), social media (Facebook, Twitter) (12%), online forums or chatrooms (8%), e-mail (6%), and online video sites (1%). Internet search engines were used by 71 participants to locate 12-step support group meetings (37%), inpatient detoxification programs (35%), short- or long-term rehabilitation programs (32%), and outpatient treatment programs (4%). Several respondents queried about medication-assisted treatments (eg, oral and extended release naltrexone, buprenorphine, methadone) (7%). Three participants used video websites (eg, YouTube) to learn about the neurological effects of substance use, strategies to maintain sobriety, and self-managing withdrawal symptoms. Participants also searched for information pertaining to withdrawal symptoms, general recovery ''tips,'' accounts and insights from ''lifers'' about maintaining sobriety (n = 3), online support communities (forums, chatrooms, social media pages, e-mail threads) (n = 3), clinical trials related to SUDs (n = 1), and scheduled supportive gatherings not affiliated with 12-step groups (eg, sober parties) (n = 1). One participant accessed their patient portal to obtain lab results and communicate with their provider.

Approximately half of participants (52%) found it difficult to navigate and obtain reliable information pertaining to their recovery or general health needs (52%). Difficulties included obtaining non-working phone numbers for addiction treatment facilities or being unable to locate treatment services within proximity. Nearly all participants understood the content (ie, ''readability'') provided online pertaining to their recovery and general health needs (95%). Finally, some participants reported accessing healthcare services to address addiction, medical, or psychiatric needs based on their online query (42%).

Online Queries for Accessing and Using Illicit Substances

Sixteen percent of participants (n = 32) utilized online platforms to locate drug dealers (38%, 17/32), obtain general information about illicit substances and prescribed medications

(22%, 7/32), safely self-administering illicit substances (16%, 5/32), understand the neuropharmacology of illicit substances (16%, 5/32), and their potential health effects (6%, 2/32). Websites facilitating contact with drug dealers included Facebook, Craigslist, and Erowid, a non-profit harm reduction and educational resource on psychoactive substances. Communication was often coded to draw attention to drug dealers and possibly avoid law enforcement by distinguishing a particular ‘‘brand’’ of heroin (eg, ‘‘Osama’’) and a possible purchase location (eg, ‘‘on Johnson Street’’).

Additional information obtained from websites included strategies to self-administer substances in a manner that would maximize its euphoric effect. Erowid provided one participant with extensive information about LSD, its neuro-pharmacology, how to self-administer the substance, and potential adverse events. Two participants accessed YouTube in order to view medical phlebotomy instructional videos and amateur footage of people who use drugs narrating how to self-administer substances intravenously. Participants also utilized online forums to locate places to use drugs or physicians that easily prescribe benzodiazepines. Commercial sites publicizing discount priced wines, ‘‘happy hour’’ drink specials at local bars, or public gatherings for drinking events were also utilized among respondents.

DISCUSSION

This descriptive survey is among the first to describe technology use patterns among a diverse sample of inpatient detoxification respondents with primarily lower levels of education, limited income, and unstable housing. Overall, these findings are encouraging as health systems prioritize technology-based interventions as a part of a multi-pronged approach to improve the identification and longitudinal care of SUDs into everyday clinical practice. Accordingly, the focus is shifting towards leveraging stand-alone or a combination of technologies that will bridge evidence-based clinical approaches (ie, pharmacotherapies, psychosocial interventions) with home, work or community settings in real-time. These study results are aligned with prior findings from emergency room (Choo et al., 2012), outpatient (McClure et al., 2013; Tofighi et al., 2015), and community settings (Collins et al., 2006) that established technology use patterns and preferences favorable to harnessing evidence-based technology-based interventions among populations with SUDs.

Mobile Phone Use Patterns

Rates of mobile phone and smartphone ownership among this sample were less than national averages (Pew Internet Research Center, 2014), but still fairly high (86%). Respondents described frequent turnover of both mobile phones (3.3) and phone numbers (2.6) during the preceding year, and exceeds mobile phone (2) and phone number (1.5) turnover among office-based buprenorphine program patients surveyed in the same hospital (Tofighi et al., 2015). Lastly, homeless participants reported significantly lower rates of mobile phone ownership (75%) compared to the rest of the sample (94%).

These results shed light on some barriers of clinic-to-patient technology-based interventions among hard-to-reach populations with SUDs transitioning from inpatient to primary care settings. Strategies to expand engagement with health information technologies include offering subsidized mobile phones and payment plans, eliciting updated contact information during clinic visits, contacting friends or family with the patient’s consent if they remain non responsive to intervention queries, expanding in-clinic access to desktop computers and tablet devices, and training patients in the use of emerging health information technologies (eg, smartphones, tablet devices, wearable sensors) (Tofighi et al., 2017; Quanbeck et al., 2018). As more Americans now access the internet via smartphones, particularly among low-income populations, smartphones are uniquely positioned to over-come barriers to accessing web-based health interventions (Smith, 2015).

Frequent use of text messaging and mobile phone features (web-browsers, camera, video) supports the integration of recent mHealth interventions utilizing ecological momentary assessments and video monitoring of pill adherence. The popularity of text messaging compared to smartphone application use in this sample reinforces the acceptability and feasibility of potential text-based interventions. Less intricate or ecologically sensitive compared with smart phone applications or biometric devices, text messaging is an effective approach to enhancing chronic disease management (eg, smoking cessation, appointment adherence, and adherence to antiretroviral therapies) (Cole-Lewis and Kershaw, 2010; Tofighi et al., 2017) with minimal back-office requirements. For example, in a recent smoking cessation study, text messaging demonstrated equal rates of smoking cessation compared with a smart phone application. (Buller et al., 2014).

Frequent episodes of misplaced, lost, or stolen phones highlight the importance of adopting privacy measures to avert the risk of compromising patient health information. Strategies may include password protection of patient electronic devices, encryption of all electronic communication, relaying only ‘‘safe’’ content (appointment reminders, medication adherence strategies) rather than laboratory results or content that may compromise patient privacy (‘‘HIV, opioids’’), promptly deleting archived messages between patients and healthcare providers (Tofighi et al., 2016a,b).

We anticipated reduced rates of smartphone ownership based on older age, homelessness, and lower income or education status based on prior surveys and possible structural barriers (McClure et al., 2013; Smith, 2015; Tofighi et al., 2015); however, only education remained significantly associated with smartphone ownership. These results reflect recent national surveys suggesting an increasing popularity of smartphone ownership among lower income populations due to the affordability of smartphones and data plans (Anderson, 2015; Smith, 2015; Pew Internet Research Center, 2014). Importantly, more Americans now access the internet using their mobile phones compared to computer or tablet devices (Tsetsi and Rains, 2017).

Computer and Internet Use Patterns

Approximately half of participants reported daily or weekly computer use and roughly a third reported computer access in their own residence. Rates of computer ownership among this sample are drastically less than the general population, (Anderson, 2015) and limit the reach of computer-delivered web-based interventions targeting SUDs among this population (Tofighi et al., 2016a,b). However, we found lower rates of internet use only among older adults despite anticipating similar findings among unemployed, non-Caucasian, and participants with lower education based on national findings and surveys among populations with SUDs (Anderson, 2015; Fox and Fallows, 2014; McClure et al., 2013; Tofighi et al., 2016a,b). Frequent internet access in public settings (eg, library, school, friends/family residence) also raises concern for transmitting sensitive content related to SUDs. These findings are aligned with national surveys reporting mobile internet usage surpassing computer-based web-browsing (Pew Internet Research Center, 2014). Such findings press for efficacy studies evaluating web-based interventions delivered via mobile phones to enhance care for populations with SUDs.

The popularity of social media and online forums or chatrooms support the use of online-based peer support net-works for individuals in recovery (Mudry and Strong, 2013). Online platforms (eg, 12-steps, SMART recovery, Women for Sobriety) offer mostly supportive and informative content that may facilitate recovery in combination with clinical-delivered interventions (Barak et al., 2009).

Health Information Search Patterns

Findings from this study indicate diverse search patterns for information related to illicit access, use, and effects of substance use. Search engines were the most popular platform to query for health services (eg, 12-step group meetings, addiction treatment services), medication-assisted treatment, and self-managing withdrawal symptoms. However, the quality of information appraised by respondents varied with frequent accounts of non-working numbers or inability to locate treatment programs within proximity. Although an observational study of retrieval strategies was not conducted, it appears that few participants were able to access readily available and reliable online sites linking participants to treatment services were limited.

We also describe accounts of procuring illicit substances using social media (eg, Facebook), Erowid, and Craigslist. Content was coded to evade any potential surveillance by law enforcement. Use of YouTube online videos also facilitated the self-administration of substances intravenously. These findings coincide with recent case reports describing the use of online websites to avoid open-air drug markets, access a broader array of illicit substances, and techniques to maximize its potential effects (Van Hout and Bingham, 2013; Tofighi et al., 2016a,b). In response, healthcare providers may utilize popular online sites to disseminate evidence-based harm reduction approaches, informational campaigns, and access to treatment services. Further studies are needed to understand how emerging platforms, including smart phone applications (eg, Tinder, Kik, Instagram, Grindr) and BitTorrent websites facilitate access to illicit substances.

Limitations

Despite describing findings from a diverse and hard-to-reach population with SUDs, several limitations must be noted. The sample size may be underpowered and preclude accurate hypothesis testing assessing the impact of selected demographic characteristics on mobile phone ownership and internet access. The generalizability of these findings may be limited due to the participation of mostly male participants, lack of recruitment among other treatment settings (eg, primary care, opioid treatment programs, residential treatment programs), and increased popularity of smartphones and other mobile devices since the study was performed. The survey was not validated and required extensive training with inter-viewers, frequent meetings to debrief and resolve any discrepancies, and observed interviews by the first author (BT) to ensure the methodological rigor of the study. The survey did not assess for participant use of the Federal Communications Commission Lifeline program, which offers subsidized mobile phone service plans for low-income individuals. Sub-sequent studies should address these limitations and assess the feasibility and clinical impact of technology-based interventions among patients enrolled in inpatient detoxification settings.

CONCLUSIONS

Addressing barriers to technology use influenced by demographic characteristics (eg, less education, older age, homelessness) may ensure effective implementation of technology-based interventions without exacerbating existing disparities in care for populations requiring treatment for SUDs. Findings also suggest the importance of tailoring combinations of technology platforms (eg, web-modules with text message reminders) rather than adopting stand-alone interventions technology-based interventions to enhance linkage and retention to office-based management of SUDs post-discharge from inpatient settings. Lastly, future studies should adopt robust intervention design approaches described by the Multiphase Optimization Strategy (MOST), the Sequential Multiple Assignment Randomized Trial (SMART), and the Technology Acceptance Model to identify optimal levels of delivering intervention components ensuring clinical impact with minimal burden to users (Collins et al., 2007).

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TABLE 1.

Demographic Characteristics (N = 206)

Variable	% (n)
Age, y	
Mean (SD)	43.68 (±11.78)
Range	22–84
Gender	
Male	91% (188)
Female	9% (18)
Race/ethnicity	
African-American	42% (87)
Caucasian	34% (69)
Hispanic	23% (47)
Other	2% (3)
Education	
Completed high school or GED	39% (79)
Some high school	29% (60)
Completed college or associate degree	23% (48)
Some college or associate degree	9% (19)
Employment	
Full-time	17% (34)
Part-time	11% (23)
Unemployed	34% (70)
Public assistance (food stamps, welfare)	17% (34)
SSI or SSD	21% (43)
Retirement	1% (2)
Insurance	
Uninsured	36% (74)
Medicaid	62% (127)
Medicare	1% (2)
Private	1% (3)
Recent incarceration (past year)	21% (44)
Residence	
Own' apartment (primary owner or rentee)	24% (50)
Family or friends	29% (59)
Halfway house	2% (5)
Homeless	45% (92)
Recent homelessness (past year)	64% (131)
Number of locations lived (past year)	
Mean (SD)	4.11 (11.91)
Range	001–99

SSD, social security disability; SSI, Supplemental Security Income.

TABLE 2.

Clinical Characteristics (N = 206)

Variable	% (n)
Alcohol	32% (66)
Daily standard drinks of alcohol (mean, SD)	22.19 (±14.98)
Age of onset (mean, SD)	16.20 (+7.43)
Opioids	53%(109)
Injected opioids, past 30 days	52%(57)
Average daily number of bags used	13.34
Age of onset (mean, SD)	24.45 (±8.45)
Co-occuring alcohol and opioid use	22%(46)
Benzodiazepine	23%(49)
Cannabis	5%(11)
Crack/cocaine	14%(29)
Other	3%(6)
Number of chronic medical conditions:	
0 or 1	70%(145)
2	19%(39)
3	6%(13)
≥4	5%(9)
Number of psychiatric conditions:	
0 or 1	90%(185)
2	7%(14)
3	3%(6)
≥4	1%(1)
Health Care utilization at Bellevue Hospital (past year)	
Primary care visits (mean, SD)	0.299 (±1.82)
Emergency department visits (mean, SD)	2.5735 (2.5729)
Inpatient detoxification admissions (mean, SD)	1.73 (1.47)

TABLE 3.

Mobile Phone Use Patterns (N = 206)

Variable	%(n)
Mobile phone ownership	86% (177)
Basic cell phone	20% (42)
Smart phone	66% (135)
Features used on mobile phone (n = 206)	
Text messaging	96% (169)
Internet	81% (143)
Camera	79% (139)
Video	64% (114)
Email	61% (107)
Social media	61% (108)
Rate of text messaging (n = 206)	
Daily	77% (137)
>1/week	11% (22)
x1/week	5% (10)
x1/month	2% (5)
x1/few months	3% (7)
Never	1% (24)
Sending or receiving text messages (n = 206)	
Very much' or 'somewhat' comfortable sending TM	82% (169)
Very much' or 'somewhat' concerned about privacy of TM	51% (105)
Preferred mode of contact TM vs Phone call (n = 206)	
TM	21% (44)
Phone call	39% (81)
Either	39% (81)
TM payment plan (n = 206)	
Flat fee for unlimited TM	83% (171)
Flat fee for limited TM	8% (17)
Pay-per-TM	4% (8)
Smart phone applications (n = 135)	65% (135)
Entertainment (eg, music, video, youtube)	45.92% (62)
Games (eg, candy crush, casino, chess)	34.81% (47)
Social media (eg, facebook, instagram, twitter)	25.2% (34)
Communication (eg, viber, skype, whatsapp)	10.37% (14)
Maps/GPS (eg, metro map)	8.15% (11)
Financial (eg, banking, tax rabbit, Indeed, paypal)	6.66% (9)
Weather	5.92% (8)
Educational (eg, encyclopedia, lumosity)	3.7% (5)
News (eg, New York Times, CNN, local news)	3.7% (5)
Retail (eg, ebay, food)	3.7% (5)

Variable	%(n)
Lifestyle (eg, tinder, happn)	2.22% (3)
Recovery applications (eg, AA or NA, cleantime counter)	0.74% (1)
Health applications (eg, WebMD)	0.74% (1)
Barriers to phone ownership, mean (SD)	
Phones owned in the last year	3.3 (2.98)
Phone numbers in the last year	2.6 (2.36)
Reasons for ≥1 phone(s) or phone number(s) in the last year (n = 158)	
Lost	63% (99)
Stolen	27% (43)
Hardware damage	21% (33)
Upgraded phone to a newer model	11% (17)
Sold for money	7% (11)
Cost	6% (10)
Given away (donated to family or friends)	3% (5)
Incarceration or arrest	2% (3)
Phone disconnected or off for more than a few hours in one day (n = 206)	
>1/day	1% (2)
Daily	5% (11)
>1/week	4% (8)
x1/week	10% (21)
x1/month	14% (28)
x1/few months	19% (39)
Never	47% (97)

TABLE 4.

Computer and Internet Use Patterns (N = 206)

Variable	%(n)
Computer use in the last 12 months	
Daily	29.61% (61)
>1/week	17.96% (37)
x1/week	6.31% (13)
x1/month	7.76% (16)
x1/few months	10.67% (22)
Never	27.66% (57)
Computer access locations	
Home	36.89% (76)
Library	32.52% (67)
Friends/family	18.44% (38)
Other	16.50% (34)
Internet use in the last 12 months	
Daily	51.45% (106)
>1/week	16% (33)
x1/week	5.82% (12)
x1/month	4.36% (9)
x1/few months	8.73% (18)
Never	12.62% (26)
Internet access locations	
Phone	66.5% (137)
Home	38.83% (80)
Library	33.5% (69)
Friends/Family	25.24% (52)
Work	5.82% (12)
School	2.42% (5)
Public wifi	2.42% (5)
Addiction treatment program	2.42% (5)
Clinic	0.97% (2)
Prison	0.48% (1)
Internet site preferences	
Social media (eg, Facebook, Twitter)	69.41% (143)
Online forums/chat rooms	52.91% (109)
Navigation (eg, Google Searches, Yahoo)	32.02% (66)
Entertainment (eg, Music, Video, Youtube)	23.3% (48)
E-mail	19.3% (39)
Educational (eg, University Webinars, Ebooks)	6.79% (14)
Retail (eg, Ebay, Craigslist, Amazon)	3.88% (8)
Games	3.88% (8)

Variable	%(n)
News	3.39% (7)
Maps/directions	2.42% (5)
Employment searches	0.97%(2)
Financial (eg, Banking)	0.97% (2)
Weather	0.97% (2)

TABLE 5.

Logistic Regression on Technology Access of Selected Baseline Demographic Characteristics (N = 206)

Variables	Adjusted Odds Ratio (95% CI) Mobile Phone	Test Statistic	P^b	Adjusted Odds Ratio (95% CI) Smartphone	Test Statistic	P^b	Adjusted Odds Ratio (95% CI) Internet	Test Statistic	P^b
Age		$\chi^2 = 5.00$	0.170		$\chi^2 = 1.30$	0.720		$\chi^2 = 8.60$	0.035
50+ years old (REF[a])									
30–49 years old	0.75 (0.27–2.04)		0.580	1.13 (0.54–2.35)		0.749	1.66 (0.88–3.14)		0.005
18–29 years old	1.83 (0.36–10.41)		0.475	1.09 (0.35–3.52)		0.883	–		0.987
Race		$\chi^2 = 8.50$	0.037		$\chi^2 = 7.50$	0.057		$\chi^2 = 6.50$	0.091
White (REF)									
Black	0.71 (0.25–1.96)		0.514	0.60 (0.27–1.34)		0.217	0.27 (0.08 –0.76)		0.020
Hispanic/Latino	4.31 (0.93–31.49)		0.09	2.06 (0.77–5.78)		0.156	0.57 (0.14–2.19)		0.418
Other	0.05 (0–0.82)		0.047	0.32 (0.01–3.93)		0.386	–		0.997
Education (%)			0.124			0.022			0.232
<High School (REF)									
≥High School	2.48 (0.83–8.78)			2.50 (1.16–5.63)			1.84 (0.70–5.24)		
Employment (%)								$\chi^2 = 7.30$	0.200
Unemployed (REF)									
Employed (full-time)	3.38 (0.33–79.13)		0.340	1.99 (0.40–11.57)		0.411	1.21 (0.21–7.70)		0.831
Part-time	0.52 (0.08–3.11)		0.48	0.47 (0.11–1.84)		0.282	3.05 (0.50–26.04)		0.251
Other[1]	0.25 (0.04–1.20)		0.098	0.32 (0.08–1.19)		0.098	1.47 (0.25–9.77)		0.673
Homeless			0.010			0.085			0.276
No (REF)									
Yes	0.11 (0.02–0.47)			0.51 (0.24–1.08)			0.60 (0.23–1.48)		