# Health-related internet use among opioid treatment patients☆

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## ABSTRACT

The Internet and smartphones have become commonplace and can be effective in overcoming traditional barriers to accessing health information about substance use disorders (SUD), and their prevention or treatment. Little is known, however, about specific factors that may influence the use of these technologies among socioeconomically disadvantaged populations with SUDs. This study characterized the use of digital technologies and the Internet among individuals receiving treatment for opioid use disorder, focusing on identifying predictors of Internet use for health-related purposes. Participants came from an urban opioid replacement therapy program and completed a face-to-face survey on Internet and technology use. We examined the association between online health information seeking and technology acceptance variables, including perceived usefulness, effort expectancy, social influence, and facilitating conditions (e.g., availability of devices/services and technical support). Participants ($N = 178$, ages 18–64) endorsed high rates of current smartphone ownership (94%) and everyday Internet use (67%). 88% of participants reported searching online for information about health or medical topics in the past 3 months. Predictors of Internet use for health-related purposes were higher technology acceptance for mobile Internet use, younger age, current employment, and less bodily pain. Our results demonstrate high acceptance and use of mobile technology and the Internet among this sample of socioeconomically disadvantaged individuals with SUDs. However, these findings also highlight the importance of identifying barriers that disadvantaged groups face in using mobile technologies when designing technology-based interventions for this population.

## 1. Introduction

The Internet and smartphones have become commonplace, and can be effective in overcoming traditional barriers to accessing health information, including information about substance use disorders (SUD), recovery-support tools and online recovery communities and forums (Bergman, Greene, Hoeppner, & Kelly, 2018; Bliuc, Best, Iqbal, & Upton, 2017; Marsch & Carroll, 2014). Internet access has steadily grown among U.S. adults from 52% in 2000 to nearly 90% in 2018 (Pew Research Center, 2017a), and smartphone ownership has more than doubled recently, from a rate of 35% in 2011 to 77% in 2016 (Pew Research Center, 2017b). Furthermore, low-income groups are more likely to rely on their smartphones to access the Internet. Recent data from the Pew Center indicated that 20% of adults whose annual income falls below $30,000 are smartphone-only Internet users as compared with only 4% of households earning more than $100,000 per year (Rainie & Perrin, 2017). The growing use of smartphones to access the Internet among lower income groups provides the opportunity to broaden the dissemination of evidence-based prevention and treatment

interventions to the most vulnerable groups that have been historically difficult to reach such as socioeconomically disadvantaged individuals with SUDs (Wu, Zhu, & Swartz, 2016).

### 1.1. Disparities in online health information seeking

While the Internet can be an important medium for disseminating health information influencing health-seeking behaviors (Mueller et al., 2017), the use of the Internet as a health information resource is much lower among disadvantaged populations. For example, a large survey of California residents, (Nguyen, Mosadeghi, & Almario, 2017) found evidence of digital disparities in online health information seeking: Elderly, racial/ethnic minority, non-English speaking, and less educated individuals were less likely to ever use the Internet or to engage in online health information seeking. Inequalities in health information seeking have also been documented by others showing that that younger people, those with higher socioeconomic status, higher level of education, and higher Internet skills are more likely to report the use of online sources for health information (Jacobs, Amuto, & Jeon, 2017). In

addition to limited Internet access, socioeconomically disadvantaged populations seeking online health information experience other barriers to information gathering such as connectivity problems and frustration during health information searches (McCloud, Okechukwu, Sorensen, & Viswanath, 2016). Health literacy, defined as "the capacity of individuals to obtain, process, and understand basic health information and services needed to make appropriate health decisions" (National Center for Health Statistics, 2011), may also play a role in determining use of the Internet for health information searches. For example, a recent study found that patients with low health literacy were less likely to use and be active consumers of health information technology (Mackert, Mabry-Flynn, Champlin, Donovan, & Pounders, 2016).

### 1.2. Use of digital technology in SUD treatment

Studies investigating SUD treatment populations have found high rates of mobile phone ownership, ranging from 83% to 95% (Ashford, Lynch, & Curtis, 2018; Dahne & Lejuez, 2015; McClure, Acquavita, Harding, & Stitzer, 2013; Milward, Day, Strang, & Lynskey, 2015; Winstanley, Stroup-Menge, & Snyder, 2018) and relatively lower rates of smartphone ownership, between 57% and 85% (Ashford et al., 2018; Dahne & Lejuez, 2015; Milward et al., 2015; Winstanley et al., 2018). While mobile phone use may be high in SUD treatment populations, there is wide variation in regular Internet use, ranging from 44% to 82% (Dahne & Lejuez, 2015; McClure et al., 2013; Winstanley et al., 2018) and using their mobile phones to access the Internet (61% to 85%) (Ashford et al., 2018; Dahne & Lejuez, 2015). Lower Internet access may reflect not owning a home computer or a lack of home broadband services; some groups still lag behind in ownership of computers and access to broadband services at home including racial/ethnic minorities, older adults, rural residents, and those with lower levels of education and income (Pew Research Center, 2017a; Smith, 2015).

Little is known about online health information seeking behaviors of individuals who have a SUD. For example, using data from a national survey of U.S. adults who resolved a substance use problem, Bergman et al. (2018) found that 11% used the Internet to access recovery-related information. In a sample of patients enrolled in outpatient SUD treatment, Ashford et al. (2018) found that the majority of respondents were receptive to mobile phone apps and text messages to support their recovery, although social media was preferred. Thus, when conceptualizing digital health interventions for SUD treatment patients, it is important to know the prevalence of technology use as well as preferences for use of digital platforms to facilitate the development of health communication tools. Without understanding the attitudes and experiences of individuals with SUDs toward technology use and online health information seeking, successful engagement and adoption of effective technologies to promote recovery among this population may be limited.

In this study we investigated the use of digital technologies and attitudes toward online health information seeking among patients undergoing opioid replacement therapy. The study findings were used to inform the design of a website to disseminate hepatitis C and HIV health information tailored to meet the needs of patients receiving opioid replacement therapy. Identifying barriers to online health information seeking can help clinicians and researchers seeking to increase uptake of the Internet for intervention delivery among patients in SUD treatment.

## 2. Methods

### 2.1. Participants and recruitment procedures

Participants were 178 opioid dependent patients recruited from a methadone maintenance treatment (MMT) program located in San Francisco in February–October 2016. Participants were recruited from the waiting room to participate in eligibility screening. Study eligibility criteria included being at least 18 years of age, currently enrolled in MMT, native English-speaking, and able to complete an hour-long interview. We over-sampled women participants and participants under 35 years of age to ensure equal representation of these groups. Those eligible for the study completed an interviewer-administered survey. Study procedures were reviewed and approved by the Institutional Review Board of the University of California, San Francisco, and a Certificate of Confidentiality was obtained from the U.S. Department of Health and Human Services.

### 2.2. Procedures and measures

Following administration of participants' prescribed methadone dose, trained research staff obtained informed consent and administered survey interviews in a private office. The survey included items capturing sociodemographic characteristics, substance use, digital technology use and attitudes, features of mobile devices, health literacy, and health status. Interviews were conducted face to face and with audio computer-assisted self-interviewing (ACASI). All survey data were recorded and tracked using Research Electronic Data Capture (REDCap), a secure web-based data collection tool, and stored on a secure server hosted at the University of California, San Francisco.

Sociodemographic information included age, race/ethnicity (White, African American, Hispanic, Asian, Native American, Other), gender, education, employment status, annual income, and whether the participant experienced homelessness in the past 6 months. Information about participants' substance use history and recent substance use was collected using the Addiction Severity Index (ASI-Lite; McLellan et al., 1992).

Items pertaining to Internet and mobile phone use were adapted from the Pew Research Internet and American Life Project survey questions on mobile phones and the Internet (Smith, 2015). Participants were asked about their frequency of Internet use in the past week, hours per day spent on the Internet using any device, primary mode of Internet access (mobile device, home computer, friends' computers, public computers), and use of the Internet to obtain health information in the past 3 months. Participants reported their mobile phone access and ownership, including whether they owned a smartphone. Those with access to a mobile phone indicated whether they used the phone to (a) send or receive text messages, (b) remind them to take their medications, (c) go online, (d) use apps, and (e) play games. Mobile phone users were also asked about their preferences for receiving health care related messages (i.e., direct contact with a provider by phone or in person, text message, email, mobile app, website, and mailed letter). Finally, frequency of interruptions to mobile phone service in the past year and details of mobile phone plans (e.g., limited or unlimited data plans/min) were examined.

Health problems were assessed with the SF-12 Health Survey Short-Form (Ware, Kosinski, & Keller, 1996). The SF-12 is a 12-item questionnaire designed to assess dimensions of health. Eight health concepts were measured: general health perceptions, physical functioning, role physical, role emotional, bodily pain, mental health, vitality, and social functioning. From the eight scales of the SF-12, scores were calculated for the Physical Component Summary and the Mental Component Summary based on factor loadings reported by Ware et al. (1996), and T-Scores for those summary scales were calculated based on published norms (Ware, Keller, & Kosinski, 1998).

Health literacy was assessed using a single item that has been effective in identifying individuals with inadequate health literacy (Chew et al., 2008). Participants were asked "How confident are you filling out medical forms by yourself?" Health literacy was measured on a scale ranging from *Not at all* to *Extremely*.

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) is a framework for understanding factors associated with the acceptance and use of new

technologies. In this study, we examined the extent to which the framework could be applied to understand mobile technology acceptance and use in the SUD treatment context. Technology acceptance and use was measured with items from four UTAUT subscales (Venkatesh et al., 2003), which covered the key constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions. All items were measured using a 7-point Likert scale from *Strongly Disagree* (*1*) to *Strongly Agree* (*7*).

The four UTAUT subscales showed adequate internal consistency according to Clark and Watson (1995). The mean inter-item correlation coefficients were $r = 0.61$ for the performance expectancy subscale, $r = 0.72$ for the effort expectancy subscale, $r = 0.56$ for the social influence subscale, and $r = 0.42$ for the facilitating conditions subscale. The four subscales were strongly correlated with each other; the mean inter-subscale correlation was $r = 0.54$. In addition, a principal components analysis of correlation coefficients among the four subscales, both from data in the current study and results reported by (Venkatesh, Thong, & Xu, 2012) revealed that the four subscales obtained high loadings on a single principal component. Since the four subscales were strongly correlated, we constructed a general UTAUT technology acceptance scale with the 13 items from the four subscales. Corrected item-total correlation coefficients ranged from $r = 0.44$ to $r = 0.81$, which according to Clark and Watson (1995) show an adequate range. The average inter-item correlation coefficient was $r = 0.45$, and Cronbach's alpha was 0.91; 85% of the inter-item correlations were moderate to high, which suggests the items measured a unidimensional construct according to (Clark & Watson, 1995).

### 2.3. Data analysis

Univariate analyses were used to describe demographic, drug use, mobile phone, and Internet use. A model-building approach was used to identify independent predictors of frequently searching for health information on the Internet in the past 3 months (6 or more times vs. less frequently). To screen for potential predictors for the final regression equation, in bivariate analyses, a separate logistic regression equation was calculated for each variable. If a bivariate logistic regression model converged, and the log-likelihood test was statistically significant at $p < .05$, the predictor was tested in a hierarchical multiple logistic regression model.

The multiple logistic regression analysis was explanatory rather than predictive (Azen & Budescu, 2009). That is, the purpose was to explain the mechanisms underlying frequent Internet health information searches, rather than to predict who makes such searches. Using hierarchical logistic regression, as outlined by (Cohen, Cohen, West, & Aiken, 2003), we entered demographic characteristics in the first set of blocks, health status in the next block, and technology acceptance in the final block. For each block, the change in deviance between blocks was examined with a log likelihood test. In a second multiple logistic regression model, we statistically controlled for everyday Internet use to rule out the possibility that frequent searching of the Internet for health information was merely an artifact of frequent Internet use, in general. As suggested by Cohen et al. (2003), experiment-wise error rates were controlled by suspending judgment for the formal hypothesis tests until the final multiple regression equation.

Analyses were conducted using R 3.4.2 (R Core Team, 2017). Logistic regression analyses were conducted with the generalized linear model (glm) procedure in the mlogit package version 0.2–4 (Croissant, 2013), colinearity diagnostics were conducted with the car package version 2.1–5 (Fox & Weisberg, 2011), and psychometric analyses were conducted with the psych package version 1.7.8 (Revelle, 2017).

**Table 1**
Sociodemographic characteristics ($N = 178$).

| Variable | $n$ | % |
|---|---|---|
| Gender | | |
| Male | 91 | 51 |
| Female | 87 | 49 |
| Race/ethnicity | | |
| Non-Hispanic White | 100 | 56 |
| African American | 32 | 18 |
| Hispanic | 19 | 11 |
| Other race/multiple | 21 | 12 |
| Native American | 6 | 3 |
| Educational attainment | | |
| At least high school | 140 | 79 |
| Employment status | | |
| Unemployed | 103 | 58 |
| Income in previous year | | |
| < $10,000 | 110 | 63 |
| $10,000–$20,000 | 38 | 22 |
| $20,000+ | 28 | 16 |
| Homeless in the past 6 months | 79 | 45 |
| Substance use history | | |
| Lifetime injection drug use | 121 | 72 |
| Illicit drug use in past month | 140 | 79 |
| Years of heroin use (mean, SD) | 9.10 | 8.78 |
| Years of methadone use (mean, SD) | 4.38 | 5.32 |
| Age (mean, SD) | 38.04 | 10.36 |
| Health status | | |
| Physical component (mean, SD) | 38.96 | 9.45 |
| Mental component (mean, SD) | 36.92 | 9.03 |
| Technology acceptance (mean, SD) | 72.78 | 12.79 |

## 3. Results

### 3.1. Sample characteristics

Table 1 presents characteristics of the study sample. The sample was racially/ethnically diverse with men and women represented in approximately equal numbers. Summary scores on the SF-12 indicate that the sample scored one standard deviation below national norms, which suggests that the sample has low physical and mental health functioning. Scores on the UTAUT scale were high relative to the logical midpoint of 52, suggesting that the sample showed high levels of technology acceptance.

### 3.2. Internet and mobile phone use

The majority of participants (87%, $n = 154$) reported currently owning a mobile phone, while an additional 13% ($n = 24$) owned a mobile phone in the past year, and 94% ($n = 167$) owned a smartphone in the past year. Over two-thirds of participants (67%, $n = 120$), accessed the Internet every day, and 74% ($n = 132$) usually accessed the Internet using a mobile device; 64% ($n = 114$) reported using the Internet every day for at least 1 h. A substantial majority of participants (88%; $n = 157$) had used the Internet to search for information about health or medical topics at least once in the past 3 months, while 52% ($n = 93$) had done so 6 or more times in the past 3 months. Most (56%; $n = 85$) reported having their current cell phone number for six months or longer. The majority of cell phone owners (74%; $n = 133$) had changed their phones one or more times in the past year, and over half (59%; $n = 104$) reported one or more service interruptions in the past year. Approximately 40% ($n = 70$) had used their mobile phone as a reminder device to take their medication, while 8% ($n = 13$) of smartphone owners had used medication management mobile apps.

### 3.3. Correlates of frequency of Internet use for health-related information

Age, current employment, bodily pain from the SF-12, health literacy, and technology acceptance as measured on the UTAUT were

**Table 2**
Predictors of frequent use of the Internet to obtain information about health or medical or topics (N = 178).

| Predictor variable | OR | 95% CI | Deviance | Deviance change | p-Value* |
|---|---|---|---|---|---|
| Age | 0.95 | [0.92, 0.98] | 234.21 | 12.19 | 0.0005 |
| Employment | 3.74 | [1.58, 9.34] | 224.90 | 9.31 | 0.002 |
| SF-12 bodily pain | 0.66 | [0.51, 0.84] | 213.48 | 11.42 | 0.0007 |
| Technology acceptance | 1.05 | [1.02, 1.08] | 203.92 | 9.56 | 0.002 |

\* Based on log-likelihood test of deviance change for the block, df = 1.

identified as potentially significant predictors of searching the Internet for health information, and thus, were examined in a multiple regression equation.

Table 2 shows the results of the hierarchical logistic regression model examining correlates of the frequent use of the Internet for health information. Age, current employment, bodily pain, and technology acceptance were significant predictors of using the Internet for health related purposes. We examined variance inflation factor (VIF) and tolerance values for each block in the hierarchical regression model, as suggested by (Field, Miles, & Field, 2013); VIF values were all lower than 10, and tolerance values were greater than 0.10, indicating that the models for each block did not violate the colinearity assumption.

Although health literacy predicted frequent use of the Internet for health information in bivariate analyses, this variable was not significant when entered as a third block in a hierarchical regression model, controlling for age and current employment. The pattern of findings in Table 2 did not change when a second hierarchical regression model was calculated with everyday Internet use entered in the first block, suggesting that the results were not an artifact of everyday Internet use.

## 4. Discussion

This study sought to learn more about the use of digital technologies and the Internet and to examine predictors of Internet use for health information among patients enrolled in an opioid replacement therapy program. Findings were that participants, who had higher technology acceptability, were younger, currently employed, and had less bodily pain were more likely to search the Internet for health information. Additionally, a high proportion (94%) of participants owned smartphones, and 67% used the Internet frequently: Fully 88% of participants had used the Internet to search for information about health or medical topics, and almost two-thirds accessed the Internet every day for at least 1 h. Besides having access to mobile devices, participants' belief that they have the knowledge or resources available to use mobile Internet contributed to a greater likelihood to use the Internet for health related purposes. Technology acceptance was high and illustrates familiarity with computers and digital devices, which may explain the high use of the Internet in general, and frequent use of the Internet to search for health information among this sample of participants in opioid addiction treatment. Similar to these results, recent studies have found high rates of smartphone ownership among methadone patients (Shrestha, Huedo-Medina, Altice, Krishnan, & Copenhaver, 2017) and more favorable attitudes toward technology-based health interventions among smartphone owners and those with unlimited data plans (McClure, Baker, Carpenter, Treiber, & Gray, 2017). Our findings highlight the high acceptability and use of the Internet for health-related purposes and extends prior research on digital technology use among those engaged in SUD treatment. This study's findings support the potential benefits of technology-based health interventions in delivering health education, particularly for populations that may be hard to reach and face more barriers to engaging in health care using traditional methods.

Although technology acceptability was high in our sample, younger age was associated with more frequently searching the Internet for health information. Some older adults may find it difficult to understand and use some of the features of mobile devices, thus influencing their decisions to engage in the use of digital health technologies (Wildenbos, Peute, & Jaspers, 2018). However, as the population of patients receiving opioid replacement therapy ages and is comprised primarily of digital natives, familiarity with computer technology may become less important than barriers related to sustained use of technology devices. Nonetheless, these issues highlight the need to address age-related differences in preferences for and experience in using digital devices when designing technology-based health education programs and interventions.

Participants with current employment were also more likely to frequently use the Internet for health related purposes. These findings emphasize the need to consider the unique needs and circumstances of people who face socioeconomic disadvantage who may experience additional challenges to accessing and using digital technologies. For example, despite high smartphone ownership in the present study, only 56% reported having their current cell phone number for six months or longer, and 59% had one or more lapses in service during the past year. Thus, although participants have access to smartphones, they may not be able to use all available features, particularly those requiring data usage. Studies examining the effects of substance use recovery interventions developed for digital platforms have offered participants free phones and replacement phones with mobile phone service plans (Guarino, Acosta, Marsch, Xie, & Aponte-Melendez, 2016; Gustafson et al., 2014) and data plans (Gustafson et al., 2014). However, this strategy may not be feasible in real-world settings (Nesvåg & McKay, 2018). Successful implementation of digital health interventions with socioeconomically disadvantaged persons in the context of addiction treatment programs will require developing strategies for financing digital health interventions. In a study examining the sustainability of the implementation of an addiction recovery support mobile app (A-CHESS), Ford and colleagues recommended establishing service lines, leveraging billing codes, and marketing the impact of digital health approaches on clients to payers as a strategy to sustain the use of digital health interventions in addiction treatment programs (Ford II et al., 2015).

Experiencing bodily pain was a predictor of frequent searches of online health information. This finding requires further study, as the analyses were exploratory, and the cross sectional design does not allow for causal inference. Further research is needed to better understand how physical and mental health status may interfere with health-related Internet use and use of Internet-based applications to support recovery in SUD populations.

It is important to note that many smartphone owners in our sample may have benefitted from state and federally subsidized programs that support mobile device and broadband access adoption among socioeconomically disadvantaged populations and reduce gaps in electronic information access (California Public Utilities Commission, 2017; Federal Communications Commission, 2017). Regional variations in public policy and program subsidies results in differential program enrollment, with California ranking higher than many other states in participation among eligible households (Universal Service Administrative Company, 2017). Information about participation in subsidized phone programs was not systematically collected in the

survey, but future studies may examine related variables to better understand the role of subsidized phone programs in influencing the attitudes toward and access of mobile technology in vulnerable populations. We also note the cultural impetus for innovation and expansion of public technologies, including wireless broadband access, in the metropolitan area in which this study took place (Lee, Hancock, & Hu, 2014). We expect that these factors reduce barriers to mobile technology use and may contribute to the relatively high rate of Internet access and use, as well as smartphone ownership, reported by study participants. Prior studies documenting lower rates of smartphone ownership among patients in addiction treatment as compared to our sample of patients receiving opioid replacement therapy were conducted in the eastern U.S. possibly reflecting regional differences in access to mobile technology (Ashford et al., 2018; Dahne & Lejuez, 2015; Shrestha et al., 2017). Furthermore, although data was collected in 2016, predictors of technology acceptability and use of the Internet for health-related information are likely stable and reflect Internet use patterns in settings that offer low-income individuals free access to the Internet.

We note other study limitations as follows: First, survey responses were elicited by participant self-report. Social desirability response bias associated with self-reported health and substance use measures may have resulted in underreporting of stigmatized health attributes and behaviors (Latkin, Edwards, Davey-Rothwell, & Tobin, 2017). Second, the survey was conducted among a socioeconomically homogenous sample in a single urban opioid treatment program, and thus future research that includes other study samples (e.g., opioid users out of treatment) or settings may be needed before the findings can be generalized to other individuals with opioid use disorders. Third, this study was exploratory and used a limited cross-sectional design, which did not allow for causal inference. A longitudinal design would have allowed us to determine the mediating role of variables such as physical and mental health functioning, employment, income or resources to use the Internet. Fourth, our recruitment strategy yielded potentially higher-than-typical proportions of women and those who were under 35 years of age. This approach, taken to examine the views of important less-represented subgroups in the SUD treatment population, introduces selection effects in our findings, which may limit generalization to typical MMT programs with older patients. Nevertheless, even after controlling for frequent Internet use, the significance of age as a predictor of higher frequency of health information seeking is notable and may reflect cohort effects in technology use within the sample.

Results of this study reveal high rates of current smartphone ownership and frequent Internet use for health-related purposes, as well as favorable attitudes toward mobile Internet. We also found evidence that online health information seeking may vary based on patient characteristics and user's perceptions related to using mobile technologies. The findings suggest the need for further investigation of mobile Internet access and patient characteristics and experiences that influence technology use among socioeconomically disadvantaged populations with SUDs. In developing technology-based interventions for, socioeconomically disadvantaged individuals with SUDs, it is essential to take into account the barriers related to access and use of digital technology. Without attention to the barriers they face, those groups may be further left behind.

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