

*Annual Review of Clinical Psychology*Mobile Health Interventions
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**Keywords**

mHealth, eHealth, digital health, just-in-time adaptive interventions, health disparities, smartphone, substance use disorders, tobacco, alcohol

Abstract

Substance use disorders (SUDs) have an enormous negative impact on individuals, families, and society as a whole. Most individuals with SUDs do not receive treatment because of the limited availability of treatment providers, costs, inflexible work schedules, required treatment-related time commitments, and other hurdles. A paradigm shift in the provision of SUD treatments is currently underway. Indeed, with rapid technological advances, novel mobile health (mHealth) interventions can now be downloaded and accessed by those that need them anytime and anywhere. Nevertheless, the development and evaluation process for mHealth interventions for SUDs is still in its infancy. This review provides a critical appraisal of the significant literature in the field of mHealth interventions for SUDs with a particular emphasis on interventions for understudied and underserved populations. We also discuss the mHealth intervention development process, intervention optimization, and important remaining questions.

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INTRODUCTION

Substance use disorders (SUDs) are commonly described as chronic relapsing disorders, which often require multiple rounds of treatment (MacKillop 2020). Traditionally, SUD treatments have involved in-person sessions with a health care provider (e.g., psychologist, counselor)

and/or group therapy sessions (e.g., Alcoholics Anonymous/Narcotics Anonymous). However, according to the 2021 National Survey on Drug Use and Health, only 6% of individuals with SUDs receive any form of treatment (Subst. Abuse Ment. Health Serv. Adm. 2023). Barriers to accessing SUD treatments include limited availability of treatment providers, cost, inflexible work schedules, lack of access to affordable childcare, treatment-related time commitments, and stigma associated with SUDs (Priester et al. 2016). Before the COVID-19 pandemic, there was a substantial shortage of SUD care providers (Murphy 2022), and this shortage has worsened since the pandemic (Panchal et al. 2023). A paradigm shift in SUD service provision is needed to overcome traditional treatment barriers and thereby increase access to and use of effective treatments (e.g., see Sweeney et al. 2022).

Much of the harm incurred from SUDs is concentrated among minoritized and disadvantaged groups. For instance, the overall prevalence of cigarette smoking has substantially decreased in the United States, yet socioeconomic, racial/ethnic, sexual/gender, rural, and mental health disparities related to tobacco use have increased (Cornelius et al. 2023). Unfortunately, underrepresentation of these groups in clinical trials has likely resulted in interventions that are less effective for certain populations. In addition, individuals from minoritized and disadvantaged groups may experience unique stressors, such as minority stress (Wolford-Clevenger et al. 2021), discrimination (Kendzor et al. 2010), and financial stress (Kendzor et al. 2010), that can hinder treatment access, engagement, and behavior change.

Over the past four decades, SUD interventions have been developed that can be delivered remotely and sometimes without the need for any human involvement through automation. Telephone-based smoking cessation counseling delivered via state-based quitlines is a prime example of successful remotely delivered interventions. Although many studies have indicated that state quitlines double smoking cessation rates (Fiore et al. 2008), recent data from the North American Quitline Consortium indicate that the number of people connecting with state smoking quitlines has declined annually over the past 7 years (N. Am. Quitline Consort. 2021). Further, one recent study in our laboratory showed that people seeking to quit smoking were approximately twice as likely to prefer smartphone-app-based interventions to telephone-based quitline counseling, three times as likely to prefer app-based interventions to individual in-person counseling, and four times as likely to prefer app-based interventions to group-based counseling (M.S. Businelle et al., unpublished data; NIH project 5R01CA221819-03). Thus, traditional in-person or telephone-based interventions may have limited and dwindling reach.

Smartphone ownership has become nearly ubiquitous in the United States: In 2021, 85% of all US adults owned smartphones (Pew Res. Cent. 2021). Substantial proportions of disadvantaged and minoritized populations own smartphones (e.g., 80% of adults with rural residence, 76% of adults with household incomes < \$30,000 per year, 85% of Hispanic adults, 83% of Black adults, and 75% of adults with less than a high school education) (Pew Res. Cent. 2021).

A diverse range of smartphone-app-based interventions for SUDs have been developed, although very few have been evaluated for effectiveness. Early app-based interventions typically delivered static content to users, who could access the content when desired. However, the substantial computing power of smartphones has more recently enabled the development of powerful, complex, and highly tailored just-in-time adaptive interventions (JITAI) (Nahum-Shani et al. 2015). Smartphone-based interventions that address SUDs may reduce barriers to accessing SUD treatments in general, and particularly among minoritized and vulnerable individuals, and thus increase the reach of effective and tailored interventions. The aims of this paper are to (a) provide a critical appraisal of smartphone-based SUD intervention research with a particular focus on interventions targeting vulnerable and understudied groups, (b) describe the JITAI development and evaluation process, and (c) discuss barriers and next steps for smartphone-based SUD interventions.

BACKGROUND

Definition of Mobile Health

Mobile health (mHealth) can be defined as health promotion interventions delivered via mobile devices, such as mobile phones, smartphones (i.e., mobile phones capable of accessing the Internet), tablets, personal digital assistants, and wearable devices (e.g., smartwatches, head-mounted displays) (Kumar et al. 2013). mHealth interventions can use data from mobile devices to actively or passively monitor substance use patterns and their internal and external antecedents and consequences (e.g., cravings, stress, motivation to stop, social context). For example, mobile devices can be used to deliver ecological momentary assessments (EMAs)—brief surveys that are meant to assess life as it is lived in people’s daily lives (“active” measurement) (Shiffman et al. 2008). Wearable sensors (i.e., passive measurement) can be used to detect substance use patterns via hand gestures (Saleheen et al. 2015), skin conductance (Carreiro et al. 2015), cardiac electrical activity (Hossain et al. 2014), or sweat evaporation (Carreiro et al. 2015). Simpler mHealth interventions may use text messaging via personal phones (i.e., basic cell phones or smartphones) to deliver intervention content. These interventions do not always require smartphone technology; such flexibility may be beneficial for populations that have lower rates of smartphone ownership (e.g., adults ≥ 65 years of age) (Pew Res. Cent. 2021).

Ecological Momentary Assessment

EMA is a research method used to repeatedly assess individuals’ behaviors, experiences, and environmental factors in real time, in naturalistic settings. EMA sampling strategies are typically time-based or event-based. Time-based sampling is solicited based on a schedule—for example, an assessment prompted every day at the same time or one prompted at random intervals (e.g., every 3–4 hours) (Shiffman et al. 2008). In contrast, event-based sampling is traditionally focused on predefined events and is typically initiated by an individual. For example, an individual may be asked to initiate an assessment every time they smoke a cigarette (Shiffman et al. 2008). EMA methodologies have several advantages over more traditional laboratory- or clinic-based sampling strategies, including (a) minimization of recall bias through the use of frequent and real-time assessments, (b) the ability to examine contextual associations between behaviors and psychological and environmental variables at a more granular level, and (c) the ability to examine behavioral trends over time and across situations and settings (Shiffman et al. 2008). Studies using EMA have shown that substance use and lapse risk in those attempting to quit are dynamic (i.e., they fluctuate over time), idiosyncratic (i.e., they differ between individuals), and driven by multiple factors (e.g., withdrawal symptoms, social context, physical context) (Businelle et al. 2016b, Koslovsky et al. 2018, Perski et al. 2023). Thus, EMAs are now a common component of JITAI or ecological momentary interventions, which aim to provide the right type and dose of support to individuals at moments of vulnerability and receptivity. While EMA allows researchers to gain valuable insights into dynamic behavioral processes, it is possible that frequent prompts for self-reports can be perceived as burdensome and disruptive.

Compliance with EMA protocols is important for accurate, unbiased sampling, yet there is no gold standard for EMA study design. Several studies have examined the impact of EMA study design features on participant compliance. In a recent meta-analysis of compliance with EMA protocols among substance users, there was no evidence that compliance rates were associated with prompt frequency, length of assessment period, or reimbursement (Jones et al. 2019). Another study, which used a pooled data set of 10 EMA studies, found that compliance declined across days and varied significantly depending on the time of day that prompts were initiated (Rintala et al. 2019). Recently, Businelle et al. employed a factorial design to identify design factors

associated with the highest EMA completion rates (NCT05194228). Participants were randomized to one of two levels on five different assessment factors: number of questions per EMA survey (15 versus 25), number of EMAs per day (2 versus 4), EMA schedule (fixed versus random), compensation strategy (compensated based on percentage of EMAs completed versus \$1.00 per EMA), and EMA response scale type (Likert versus slider). Results revealed no significant main effects of any design factor on compliance; however, several demographic characteristics, including younger age, history of a substance use problem, and probable current depressive disorder, were associated with lower EMA compliance rates over the 28-day assessment period.

Just-in-Time Adaptive Interventions

JITAI typically use mobile devices (e.g., smartphones, smartwatches) and incorporate data from one or more data streams [e.g., EMA, global positioning system (GPS), heart rate] to inform dynamic interventions. According to one framework (Nahum-Shani et al. 2018), JITAI consist of (a) decision points, which are time points when an individual may be receptive to an intervention, (b) tailoring variables, which include inputs about psychological or contextual factors that inform decisions about when and how to intervene, (c) intervention options, which are various behavior change strategies or delivery modes, (d) decision rules, which are systematic links between decision points, tailoring variables, and intervention options, (e) proximal outcomes (e.g., current or near-term psychological distress), and (f) distal outcomes (e.g., smoking abstinence at 6 months). JITAI provide intervention content that is tailored to each user, thus potentially increasing the perceived personal relevance and usefulness of interventions. JITAI may overcome barriers that have limited the uptake of and engagement with traditional interventions and, more recently, static mHealth interventions (Perski et al. 2017a).

Advantages and Disadvantages of Mobile Health Interventions

There are many advantages, and some disadvantages, of mHealth interventions. One disadvantage is the potential lack or attenuation of the therapeutic alliance or relationship that can be developed between a patient and therapist during traditional phone-based or in-person counseling (Baier et al. 2020). However, perhaps surprisingly, recent research has indicated that mHealth users may develop therapeutic relationships with smartphone apps (Hébert et al. 2020, Tami-Maury et al. 2022). Another potential disadvantage is that although smartphone ownership is nearly ubiquitous in the United States, approximately 15% of US adults do not own smartphones (Pew Res. Cent. 2021). Notably, older adults (aged 65+ years) are the least likely (of the subgroups assessed) to own smartphones (61% ownership), and other disadvantaged and/or minoritized groups have slightly lower rates of smartphone ownership relative to the general US population [e.g., annual income < \$30,000 (76%), education < high school (75%)] (Pew Res. Cent. 2021). Nevertheless, basic cell phone interventions, such as text-messaging or telephone counseling interventions, can potentially fill this gap for these subpopulations, as $\geq 92\%$ of adults aged ≥ 65 years, with incomes < \$30,000 and education < high school, own a basic cell phone or smartphone (Pew Res. Cent. 2021). It is also noteworthy that smartphone ownership has increased dramatically from 35% in 2011 to 85% in 2021 (Pew Res. Cent. 2021) and will presumably continue to increase in the years ahead. In addition, barriers to traditional in-person or telephone counseling (e.g., lack of transportation or childcare, inflexible work schedules) likely affect more people than the lack of smartphone ownership. Further, smartphone ownership outpaces access to phone landlines and to tablet or desktop computers that support phone- or web-based SUD counseling or telemedicine sessions (Pew Res. Cent. 2021).

These disadvantages notwithstanding, mobile phones in general and smartphones in particular may increase the reach of SUD interventions and reduce the burden associated with in-person

interventions. For example, individuals living in rural areas may have limited access to nearby SUD treatments (Murphy 2022). Other barriers, such as work requirements, costs, and unmet needs for affordable childcare, increase the difficulty of seeking and participating in SUD treatments (Priester et al. 2016). In contrast to in-person interventions, many mHealth interventions are available 24/7 and can be used whenever individuals need them, increasing autonomy and accessibility. In addition, mHealth interventions can reach individuals across settings and contexts without requiring travel or childcare. Further, mHealth interventions may reduce the impact of stigma on treatment participation because participants do not have to attend treatment visits at a clinic or engage in face-to-face treatment interactions with others, allowing the individual to access the intervention when they are alone and away from the potential judgment of others. Also, mHealth interventions may enable assessment and triage of patients with more substantial needs, thus reserving health care professionals' time for more complex cases that need intensive care and attention. mHealth interventions can be paired with other remotely delivered interventions (e.g., counseling via telephone or video conferencing, mailed pharmacotherapy) for individuals and groups who may benefit from more intensive therapies (Vidrine et al. 2022). mHealth interventions can also enable access to tailored and intensive intervention content for extended periods of time (e.g., years, decades). Finally, mHealth interventions can use algorithms to increase or reduce the intensity of care based on an individual's needs or preferences. For example, mHealth interventions could inform wellness programs by querying individuals weekly or monthly about personal health improvement goals and providing on-demand and prompted support.

OVERVIEW OF MOBILE HEALTH INTERVENTIONS FOR SUBSTANCE USE DISORDERS

In this section we provide a brief overview of mHealth interventions that have been developed for specific SUDs.

Tobacco

Several systematic reviews have been conducted that examine the performance of mHealth interventions for smoking cessation (Barroso-Hurtado et al. 2021, Sha et al. 2022, Whittaker et al. 2019). Most recently, Sha and colleagues (2022) reported that automated digital smoking cessation interventions ($N = 19$ reviewed) achieved greater smoking cessation rates than self-help and no-intervention control interventions. In fact, the authors indicated that automated digital smoking cessation interventions could increase successful smoking cessation by 50% compared with self-help and no intervention. Interventions were most likely to be developed based on the trans-theoretical model and cognitive behavioral theory, though neither had a differential association with smoking cessation. Another recent review of 24 mHealth interventions for smoking cessation highlighted common features of stand-alone smoking cessation apps and apps with a face-to-face component and concluded that there is not adequate evidence that apps with a face-to-face component outperform stand-alone smoking cessation apps (Barroso-Hurtado et al. 2021). Other reviews have indicated that there is “moderate-certainty evidence” that automated text-messaging interventions increase quit rates compared with minimal interventions (Whittaker et al. 2019).

Few fully powered randomized controlled trials (RCTs) have examined the utility of mHealth interventions. One recent exception is the iCanQuit trial. In just 16 months, Bricker and colleagues (2020) recruited a nationwide sample of 2,415 adults who wanted to quit smoking and randomized these participants to the iCanQuit or the National Cancer Institute's (NCI's) QuitGuide intervention. The iCanQuit intervention is based in acceptance and commitment therapy (ACT), which teaches acceptance rather than avoidance of smoking triggers. Results indicated that those assigned

to the iCanQuit intervention had self-reported smoking abstinence rates that were significantly higher than those assigned to the QuitGuide intervention (28.2% versus 21.1%; $p < 0.001$).

Cannabis

Few evidence-based mHealth interventions are available for individuals who want to quit or reduce their cannabis use. A content analysis of 59 cannabis-related mobile apps on iOS and Android revealed that most apps provided information about cannabis strain information, dispensary locations, or recipes, and none addressed addiction or treatment (Ramo et al. 2015). Several small pilot studies have examined the preliminary effectiveness of mHealth apps specifically designed for those who want to abstain from cannabis use. A systematic review of mHealth interventions for SUDs identified three studies that focused on cannabis (discussed in more detail below), which reported positive treatment efficacy results (Carreiro et al. 2020). Albertella and colleagues (2019) pilot-tested a smartphone-app-based intervention for adult cannabis users who wanted to quit or reduce their use. The intervention included features such as personalized feedback about each participant's cannabis use, development of a quit plan, progress tracking, and tips for coping with lapse triggers. The intervention was found to be feasible and acceptable, and participants showed significant reductions in cannabis use and dependence. Another recent study examined the feasibility and preliminary efficacy of a JITAI to reduce marijuana use among youth (Shrier et al. 2018). Patients aged 15–24 who used marijuana at least three times per week received two sessions of in-person counseling and were randomized to receive a JITAI to increase motivation to reduce marijuana use (i.e., the MOMENT intervention), EMA only, or no further treatment. Results indicated that the MOMENT intervention was feasible and acceptable, and marijuana use was less likely in the MOMENT and EMA-only groups compared with the no-treatment control group.

Alcohol

The evidence base for mHealth interventions designed to reduce alcohol consumption is rapidly growing: Several systematic reviews have been published, although meta-analyses remain rare. A meta-analysis of 10 RCTs of text-message interventions found positive effects on the number of self-reported episodes of heavy drinking per month and weekly alcohol consumption; however, estimates included the null, and the quality of evidence was judged to be low (Bendtsen et al. 2021). The authors argued that small effects are nontrivial at the population level (assuming potential wide adoption of low-burden text-message interventions). Several systematic or scoping reviews have summarized evidence for basic cell phone and smartphone-app-based interventions targeting hazardous alcohol use and/or alcohol use disorders (AUDs) across various populations (e.g., university students, community-dwelling adults) (Berman et al. 2016, Colbert et al. 2020). Overall, there has been mixed evidence of effectiveness, which indicates the need for additional high-quality trials.

One systematic review that focused on personalized digital interventions more broadly (e.g., laptops, phones, tablets) found moderate- to low-quality evidence that digital interventions can help reduce alcohol consumption (average reduction of approximately three UK standard drinks per week) (Kaner et al. 2017). In addition, low-quality evidence from a smaller subset of studies suggested no major differences in impact on alcohol consumption between interventions delivered digitally and those delivered face-to-face (Kaner et al. 2017). One seminal example of an alcohol-related JITAI is A-CHESS, which was developed for individuals transitioning from residential to outpatient alcohol treatment (Gustafson et al. 2014). The intervention was designed to enhance perceived competence, social relatedness, and motivation to reduce alcohol consumption through self-assessments, discussion groups, counselor support, links to online resources focused on

addiction management, GPS tracking to prompt patients if they approached a high-risk location, and personalized goal setting (Gustafson et al. 2014). A-CHESS has demonstrated efficacy across multiple studies (e.g., McKay et al. 2022).

Other Substances

A few systematic or scoping reviews have summarized the available evidence for mHealth interventions that target SUDs more broadly (e.g., opioids, cocaine, methamphetamine, polysubstance use). Although early evidence supports the acceptability and feasibility of such interventions, few RCTs have been conducted, and no meta-analysis is available (Staiger et al. 2020, Tofghi et al. 2017). Regarding JITAIs that have specifically targeted illicit substances, findings were summarized in 2022 via a systematic review, which concluded that evidence is currently mixed and that large-scale evaluation studies are lacking (Perski et al. 2022). In the next section, we review mHealth interventions for SUDs in vulnerable and underserved populations in greater detail.

MOBILE HEALTH INTERVENTIONS FOR VULNERABLE POPULATIONS WITH SUBSTANCE USE DISORDERS

Special considerations may be needed when developing mHealth interventions for underserved and vulnerable populations. To that end, Lee and colleagues (2022) suggested the following key principles: (a) develop a strategy to address communication inequalities, (b) engage stakeholders early on, (c) build in privacy safeguards and be transparent with privacy–utility tradeoffs, and (d) balance science with the protection of vulnerable populations. Some findings indicate that mHealth interventions may be particularly appealing in vulnerable groups. For instance, one study showed that a high proportion of individuals from subgroups experiencing tobacco-related health disparities [e.g., sexual and gender minority (SGM) individuals, people with low income, people with a history of psychopathology, individuals with Medicaid insurance, rural residents] activated and used a free tobacco cessation app offered alongside a state quitline (Fradkin et al. 2022). Greater attention should be paid to developing mHealth interventions for populations experiencing health disparities, both inside and outside the United States, and support is needed to create mHealth infrastructure in low- and middle-income countries (LMICs) (e.g., see McCool et al. 2022).

Socioeconomically Disadvantaged Adults (Low Socioeconomic Status)

Several insights were shared in a recent scoping review of eHealth lifestyle interventions for people with low socioeconomic status (SES) (Al-Dhahir et al. 2022). Although the review did not focus solely on interventions for SUDs, most interventions included tailored content based on preferred language, digital literacy, user characteristics, or context-specific situations. Overall, individuals with low SES found eHealth interventions acceptable, and the interventions were most likely to employ multimedia, self-monitoring, tips, social support (e.g., via text messages or social media), reminders, and incentives. Barriers to the use of eHealth interventions included technical difficulties, limited digital skills among users, low literacy, and limited time and motivation among users. Facilitators of use included simple and relevant content, the provision of devices, human coaches, self-monitoring, social support, and a variety of other factors.

Text-messaging interventions have been developed and evaluated for socioeconomically disadvantaged adults. This type of intervention has the potential to reach the 97% of people who own any type of mobile phone in the United States (Pew Res. Cent. 2021). Vidrine and colleagues (2019) reported that tailored text messaging combined with nicotine replacement therapy (NRT) and counseling was associated with more than double the smoking abstinence rates compared

with NRT alone or NRT plus tailored text messaging among socioeconomically disadvantaged adults. Likewise, findings suggested that more intensive interventions (i.e., telephone counseling) combined with mHealth interventions and traditional NRT may optimally improve cessation. Another study showed that mobile-phone-delivered messaging and standard care (e.g., advice to quit, NRT, and printed self-help materials) for smoking cessation were cost-effective, but the addition of telephone counseling demonstrated even greater cost-effectiveness for low-income adults (Daly et al. 2019). Spears and colleagues (2019) demonstrated the initial feasibility and acceptability of a mindfulness-based smoking cessation intervention that included group mindfulness-based addiction treatment, NRT, and text messaging (iQuit Mindfully) among low-income adults. In addition, semistructured interviews of participants have identified mHealth factors that facilitate or hinder engagement, which may inform future refinements of interventions, including helpful aspects of treatment (e.g., personalization, social support), unhelpful/disliked aspects (e.g., repetitive/too many messages), creation of links between in-person sessions and texts, and other suggestions (e.g., include more personalization, change the timing/volume of messages) (Cottrell-Daniels et al. 2022).

Likewise, smartphone-based JITAIs for smoking cessation have been developed and evaluated for socioeconomically disadvantaged adults. Businelle and colleagues (2016a) developed the Smart-T app, which used participant responses to five daily EMAs to drive an algorithm that triggered messages tailored to each individual's current level of smoking lapse risk and lapse triggers (e.g., urge to smoke, stress) among safety net hospital patients. Smart-T offered additional intervention features on demand (e.g., one-click access to the tobacco cessation Quitline, "Quit Tips" on coping with mood, stress, and urges to smoke). Results indicated that engagement with the Smart-T app was high (e.g., 83% used the on-demand content), and acceptability was demonstrated (e.g., 97% would like to use the app in the future if they were to lapse). In addition, 20% of the sample were biochemically confirmed abstinent at 12 weeks after the scheduled quit date. Only 15% of participants indicated that the frequency of the intervention assessments (i.e., five daily EMAs) was too high. The Smart-T intervention was further tested in a three-arm pilot RCT that compared the Smart-T2 app with tobacco cessation counseling and the NCI QuitGuide intervention in primarily low-SES adults (Hébert et al. 2020). Results indicated that the Smart-T2 app performed at least as well as these comparators: Biochemically confirmed abstinence rates at 12 weeks after the scheduled quit date were 22% for those assigned to the Smart-T2 intervention, 15% for those who received traditional in-person or phone-based counseling, and 15% for those assigned to the NCI QuitGuide intervention ($p =$ not significant). A full-scale trial of the Smart-T intervention is underway (expected to complete in 2024) among adults with a household income below 200% of the poverty threshold (NIH project 5R01CA221819-03).

Santiago-Torres and colleagues (2022b) evaluated the efficacy of a novel smartphone app based on ACT for smoking cessation (iCanQuit) among low-income adults compared with the NCI QuitGuide app. Findings indicated that both self-reported cessation rates and app use were greater for the iCanQuit app relative to QuitGuide, and this relationship was mediated by increased acceptance of cues to smoke. Interestingly, the investigators demonstrated the efficacy of iCanQuit alone without additional counseling or provision of pharmacotherapy (although pharmacotherapy was recommended in the app).

Thompson and colleagues (2020) conducted a pilot RCT of a smartphone app (OnTrack) designed for self-monitoring of substance use and sexual risk behaviors combined with a brief motivational intervention. The goal of the intervention was to reduce substance use and sexual risk among young adults experiencing homelessness. OnTrack was compared with treatment as usual at an inner-city crisis shelter. Findings indicated that participants assigned to the OnTrack intervention significantly reduced self-reports of number of drinks, marijuana use

episodes, occasions of unprotected sex, and occasions of drug use before sexual activity. No reductions in substance use or sexual risk behaviors were found among participants assigned to treatment as usual.

AJITAI called Smart-T Alcohol was developed and pilot-tested for adults with AUDs who were also experiencing homelessness (Walters et al. 2022). Participants completed brief EMAs each day, which prompted personalized treatment messages tailored to their current risk of drinking based on a predictive algorithm that previously had been shown to predict over 80% of drinking occasions within 4 hours preceding the first drink of the day (Mun et al. 2021). In addition, participants could access on-demand intervention content that included tips focused on topics such as managing urges, coping with mood, living a healthier lifestyle, and increasing safety. In the initial pilot study, participants showed decreases in daily drinking, drinks per day, and heavy episodic drinking over 4 weeks (Walters et al. 2022).

Finally, Kendzor and colleagues (2020, 2022) have used mHealth apps to increase the reach of incentive-based interventions for smoking cessation among socioeconomically disadvantaged adults. The PREVAIL intervention verifies identity (via facial recognition software) and smoking status (via remote breath sample submissions) and automatically initiates incentive payments to a credit card when self-reported smoking abstinence is confirmed. This incentives-based intervention has been combined with tobacco cessation counseling and pharmacotherapy to provide an intensive intervention approach that can reach people regardless of their proximity to a clinic. The initial feasibility of this approach has been described along with challenges (e.g., facial recognition, sustained engagement) (Kendzor et al. 2020), and a fully powered RCT is underway.

Racially/Ethnically Minoritized Populations

Businelle and colleagues (2022) are currently evaluating and refining a mobile smoking cessation app [i.e., Mobile Anxiety Sensitivity Program for Smoking (MASP)] that targets anxiety sensitivity among Black people who smoke cigarettes. The app-based intervention is designed for use with combination NRT (patches and lozenges). The app includes 16 brief culturally tailored videos delivered over 6 weeks, treatment messages tailored for current lapse risk factors (assessed via EMAs), on-demand and scheduled tips and exercises (e.g., managing cravings, stress, and mood), and a coping toolkit (e.g., guided relaxation and mindfulness exercises). MASP is currently being evaluated against the NCI QuitGuide intervention in an RCT.

Santiago-Torres and colleagues have evaluated the iCanQuit smoking cessation app (described above) relative to the NCI QuitGuide app in subsamples of American Indian/Alaska Native (Santiago-Torres et al. 2022c), Hispanic (Santiago-Torres et al. 2022e), and Black (Santiago-Torres et al. 2022d) participants who were enrolled in the parent RCT. Overall, self-reported cessation rates were higher among those assigned to the iCanQuit app across follow-ups, though statistical significance varied somewhat by the specific cessation outcome being evaluated and depending on the follow-up time point. As in the parent study, treatment effects were mediated by acceptance to internal cues. The iCanQuit app demonstrated preliminary efficacy for smoking cessation, even though it was not specifically tailored for any particular racial/ethnic group. Other formative work has focused on the development of smoking cessation apps for other racial/ethnic groups, including Korean American emerging adults (Cerrada et al. 2017) and Vietnamese speakers in the United States (Le et al. 2023).

Notably, qualitative research has characterized preferred features of smoking cessation apps among Black people who smoke, including information about the health and financial benefits of quitting, testimonials, interactive elements, tracking of smoking, tailored feedback and personalization, reminders, access to social networks, and the inclusion of content that is specifically relevant for Black people (e.g., statistics, images) (Enyioha et al. 2023). The findings of a

focus group study of Black and Hispanic men living with HIV with recent antiretroviral therapy nonadherence and methamphetamine use illuminated confidentiality concerns (i.e., HIV status, methamphetamine use, legal consequences) and assessment-triggered substance cravings in smartphone-based research (Pasipanodya et al. 2020). Findings highlight the need to understand and address barriers to mHealth research participation in vulnerable groups.

Individuals Experiencing Mental Illness

Several smartphone-based interventions have been developed for adults with mental illness (Chen et al. 2023). For example, Vilardaga and colleagues (2018) developed their Learn to Quit smartphone-based smoking cessation intervention for adults with serious mental illness. User-centered design (UCD) methods were used to develop a tailored app that incorporated evidence-based content [i.e., ACT, Clinical Practice Guidelines for the Treatment of Tobacco Use and Dependence (Fiore et al. 2008)], behavioral principles, simple features to facilitate comprehension of smoking cessation content, gamification, stories and visuals, and access to technical coaching. Preliminary evaluations of the intervention indicated greater engagement, usability, reductions in smoking, and abstinence rates for Learn to Quit versus the NCI QuitGuide intervention (Browne et al. 2021). Lawn and colleagues (2018) described a protocol for the adaptation and pilot-testing of the Kick.it app for young adults with serious mental illness. The app includes access to a social network and encourages the logging of smoking and craving, which triggers educational content. Minami and colleagues (2018) developed a smartphone-assisted mindfulness-based smoking cessation intervention that included contingency management among adults receiving outpatient treatment for mood disorders. Preliminary feasibility data demonstrated high levels of engagement with the assessment and intervention components, and participants reported overall satisfaction with the intervention. Wilson and colleagues (2019) developed a mobile smoking cessation intervention for individuals with schizophrenia, schizoaffective disorder, and psychotic disorder, and they established evidence of initial acceptability and preliminary effectiveness. The intervention included mobile contingency management, smoking cessation pharmacotherapy, cognitive behavioral counseling sessions, and the Stay Quit app for relapse prevention. Gowarty and colleagues (2021) characterized the usability and acceptability of the NCI QuitGuide and quitSTART smoking cessation apps among young adult tobacco users with serious mental illness who were not currently interested in quitting. While both apps demonstrated acceptable usability, participants showed greater engagement with the quitSTART app. Importantly, most of these smartphone-app-based interventions are in the early stages of development and evaluation, and larger-scale RCTs will be needed to establish efficacy and effectiveness.

Minoritized Sexual Orientation/Gender Identity

mHealth intervention research has begun to focus on SUDs among SGM individuals. For instance, Baskerville and colleagues (2016) described the perceptions of a culturally tailored mobile app for smoking cessation among LGBTQ+ (lesbian, gay, bisexual, trans, queer, and other sexual minority) youth and young adults. Participants appreciated the accessibility, monitoring, connection with the community, tailoring, social networks, and personalization of the mobile app. However, they expressed concerns about privacy, some people not owning smartphones (2016 data), and lower interest in the app over time. Heffner and colleagues (2021) described the development and preliminary evaluation of an avatar-led, ACT-based digital intervention for smoking cessation designed for SGM young adults called Empowered, Queer, Quitting, and Living. Initial findings supported the acceptability and preliminary efficacy of the intervention. Likewise, Tami-Maury and colleagues (2022) recently described a protocol for the development of a

text-messaging-based intervention for SGM individuals (SmokeFreeSGM). The development of the intervention will include a community advisory board to guide the study design, beta-testing of the intervention with SGM individuals, a feasibility trial with SmokeFreeTXT as the comparison group, and qualitative interviews to assess acceptability.

Low- and Middle-Income Countries

Although mobile device access and connectivity have historically been limited in many LMICs, coverage and access have rapidly improved (Taylor 2023). Despite this increased accessibility, mHealth interventions for SUDs in these countries remain rare; the available examples primarily target smoking cessation (McCool et al. 2022). For example, the Takore i te Kai Ava'ava (Quit smoking) program culturally adapted an existing intervention to suit the needs of people living on the island of Rarotonga who wanted to quit smoking. It was found to be highly acceptable and potentially cost-effective (Ringi et al. 2021). Mhurchu and colleagues (2019) developed and evaluated a mobile intervention (OL@-OR@) in collaboration with Māori and Pasifika communities in New Zealand. The app contained culturally relevant information, concepts, and images, and participants could set goals related to alcohol and tobacco use behaviors that they wanted to track and change. Participants received virtual rewards when they achieved their goals. A minority of participants (26%) set a behavior change goal, and no difference in adherence to recommended alcohol- and tobacco-related guidelines was found between the intervention and control groups (although both groups improved their adherence to substance use guidelines from baseline to 12-week follow-up). The Be He@lthy Be Mobile program, a collaboration between the International Telecommunications Union and the World Health Organization, was founded in 2012 and includes the mCessation and mTB-Tobacco guidelines, which outline the processes involved in the implementation of mHealth smoking cessation programs in LMICs (World Health Organ. 2015). As part of this initiative, in 2018, 2.1 million people who smoked had signed up for India's mCessation program. According to a rapid horizon-scanning review of digital alcohol reduction interventions, aside from one study conducted in Brazil, there were no studies conducted in LMICs (Field et al. 2019).

Other Vulnerable Populations

Little attention has been paid to mHealth interventions for SUDs in other vulnerable populations, including individuals living with chronic conditions (e.g., HIV) and those living in rural areas. The iCanQuit smoking cessation app (described above) has demonstrated initial promise among adults residing in rural areas who may have limited access to more traditional tobacco cessation interventions (Santiago-Torres et al. 2022a). Shuter and colleagues (2018) evaluated a text-messaging intervention and website with brief treatment videos (Positively Smoke Free-Mobile) for smoking cessation among people living with HIV. Daily text messages offered motivational and inspirational quotes, smoking cessation tips, requests for pledges to stay quit, and check-ins regarding smoking status. Participants could also text the letters C-R-A-V-E to receive tips for coping with cravings. In addition, all participants were provided with 3 months of nicotine patches. Overall, participants demonstrated good engagement with the intervention, and greater age and non-Black race were associated with greater app engagement. Participants found the intervention to be acceptable, and preliminary efficacy was supported. Likewise, the Lumme mobile app plus smartwatch for smoking cessation combined counseling and NRT and was pilot-tested in a sample of people living with HIV (Schnall et al. 2022). The smartwatch learned to detect hand movements associated with smoking over a 2-week period and then was able to predict cravings and deliver timely messages and track smoking behavior over time.

Cultural Tailoring

A large body of evidence suggests that health behavior interventions tailored on individual-level factors (e.g., demographic characteristics, behaviors) are more effective than generic interventions (Noar et al. 2007). Cultural tailoring, or “adapting the intervention to reflect cultural needs and preferences” (Joo & Liu 2021), is often used in health behavior interventions targeting racial/ethnic minorities, and content is typically modified to reflect the language, beliefs, and health behaviors of the target population. Some have argued that the recent advances in precision behavioral interventions (e.g., JITAIs) have made previous cultural tailoring strategies obsolete (Kim et al. 2022b). Rather than tailoring on broad characteristics such as race/ethnicity, JITAIs allow for highly specific individual-level intervention strategies that target not only static demographic characteristics but also dynamic characteristics such as affect, psychosocial context, environment, and prior responses to treatment. Given that understandings of cultural identity are complex and evolving (Chao & Moon 2005), that individuals often have identities that span across multiple cultures, and that there is wide heterogeneity within cultures, individual-level tailoring may prove more beneficial than cultural tailoring. Additional research is needed to determine the impact of cultural tailoring in mHealth interventions.

A SEVEN-STEP APPROACH TO DEVELOPMENT OF JUST-IN-TIME ADAPTIVE INTERVENTIONS

The development and rating process for mHealth interventions has been previously discussed (Sharma et al. 2022, Stephan et al. 2017, Stoyanov et al. 2015). Although several JITAIs targeting SUDs have been developed (with some, as discussed in the above section, specifically designed for underserved populations), the JITAI development process is still relatively new and opaque and has not yet been well articulated. In this section, we discuss one approach to JITAI development and evaluation.

Businelle and colleagues (and others) have taken an approach to JITAI development that involves the following steps (see **Figure 1**). First, a literature search is conducted to identify and select variables that may predict outcome(s) of interest (e.g., smoking lapse, imminent alcohol use) (Businelle et al. 2010, 2013). Second, a 2- to 6-week observational study is designed and conducted that includes multiple daily EMAs to identify relations between predictor variables and the outcome(s) of interest over relatively short time scales (e.g., 4 hours) (Businelle et al. 2014, 2016b; Hébert et al. 2021a; Koslovsky et al. 2018; Santa Maria et al. 2018). Third, various strategies (e.g., machine learning, Bayesian continuous-time hidden Markov models, elastic net penalized Cox proportional hazards regression) are used to develop parsimonious algorithms

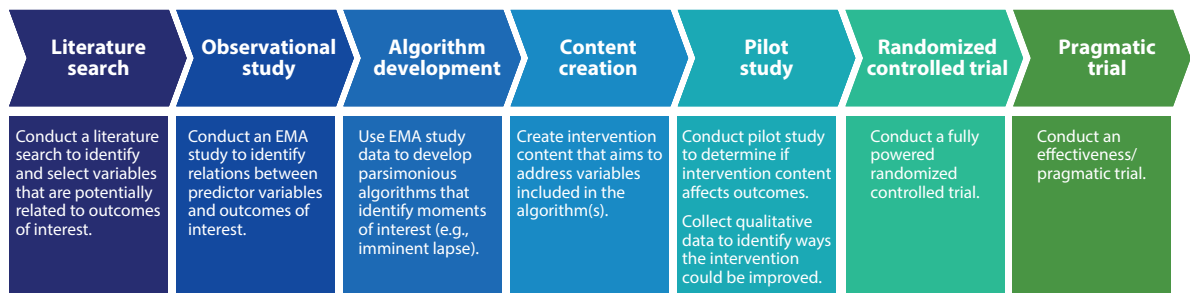


Figure 1

A seven-step approach to JITAI development. Abbreviations: EMA, ecological momentary assessment; JITAI, just-in-time adaptive intervention.

that include a reduced number of items (e.g., EMA questions, sensor data, places) to effectively identify moments where risk for undesired outcomes (e.g., smoking, alcohol use) is imminent (Businelle et al. 2016b, Hébert et al. 2021b, Suchting et al. 2019). Fourth, intervention content (e.g., text-based messages, short videos) aiming to attenuate or address antecedents (e.g., smoking urges, stress) of undesirable outcomes is developed and integrated into a new intervention (Businelle et al. 2020, 2022; Garey et al. 2022b; Walters et al. 2022). A pilot RCT is then conducted to determine whether the intervention has the desired effects on the targeted outcomes and proposed mechanisms (Businelle et al. 2016a; Garey et al. 2022a; Hébert et al. 2018, 2020; Santa Maria et al. 2021). During the pilot RCT, qualitative interviews are commonly employed to inform potential future improvements to the intervention (e.g., identify liked or disliked intervention content and features, identify important content that should be added) (Acorda et al. 2021, Businelle et al. 2022, Charron et al. 2023). Next, the intervention is modified based on the results of the pilot RCT, and a fully powered efficacy RCT is conducted. Finally, if results are promising, an effectiveness/pragmatic trial can be designed and conducted. It is important to note that few pragmatic trials have been conducted to date, largely because few JITAIs that address SUDs have made it past the efficacy evaluation phase.

BARRIERS TO THE WIDESPREAD ADOPTION OF MOBILE HEALTH INTERVENTIONS

In this section, we consider broad challenges to the adoption of mHealth interventions in general and of JITAIs in particular.

mHealth interventions for SUDs cannot achieve their targeted outcomes if they are not utilized. Yet, evidence from representative population-level surveys has indicated that the uptake of mHealth interventions is low (Perski et al. 2019b). When mHealth interventions are used, they have been shown to be effective in population-level studies, particularly in socioeconomically disadvantaged groups (reviewed above). At present, users most commonly find and download apps through unregulated digital marketplaces, such as the Apple App Store or the Google Play Store (Perski et al. 2017a). Evidence from research using both quantitative and qualitative methods has highlighted that the uptake of health-focused apps is influenced by several factors, including availability at low cost; recommendations from friends, family, and/or health care providers; perceived utility; relevance and accuracy of the intervention; transparency about data protection; the immediate look and feel of the intervention; and the intervention's perceived quality as judged by brand recognition and other users' ratings in digital marketplaces (Perski et al. 2017a). Potential strategies for the dissemination of evidence-informed mHealth interventions beyond digital marketplaces are discussed below.

Again, to benefit from mHealth interventions, users must engage with them (engagement is defined as the extent of intervention usage and a subjective experience characterized by attention and interest) (Perski et al. 2017b). A positive association between engagement and intervention effectiveness has been observed across multiple studies (Donkin et al. 2011), and although this relationship is likely to be partly driven by self-selection or attrition bias, it is reasonable to assume that at least some exposure to an mHealth intervention's active ingredients is necessary for behavior change to occur. Consumer surveys have estimated that about a quarter of available health and fitness apps are used only once by each user and that fewer than 1 in 10 use the app 7 days after the app is downloaded (Grennan 2016). Studies investigating factors that promote or detract from engagement with mHealth interventions in general and with JITAIs in particular have highlighted the following design features as key: tailoring of goals and feedback, a nonjudgmental communication style, privacy, accuracy, and embedded health care professional support. However, a review of JITAIs to reduce harmful substances found that few JITAIs had been integrated

with substance use services to facilitate embedded health care professional support (Perski et al. 2022).

Once an mHealth intervention has been developed and evaluated in a large RCT with favorable results, it is important to widely disseminate the intervention. In the early days of mHealth research, the scale-up of interventions tended to be based on models used in the pharmaceutical industry and public health—that is, controlled effectiveness studies followed by implementation studies (Murray et al. 2016). However, given the rapidly changing landscape of mHealth interventions and the increasing involvement of interdisciplinary and intersectoral stakeholders, additional approaches to the widespread dissemination of mHealth interventions have begun to surface. Three novel approaches are outlined below, although this list is not exhaustive. First, as many mHealth interventions can (both technically and legally) be distributed through commercial app marketplaces (e.g., the Apple and Google Play App Stores), they can reach millions of potential users. This approach has, for example, been used by the Smoke Free (Crane et al. 2019) and Drink Less apps (Garnett et al. 2021). Early versions of the apps were released onto the app marketplaces following initial vetting by experts and usability testing, and subsequent optimization and evaluation studies were conducted directly within the app marketplace context. For example, an optimization study that tested the added value of a chatbot to the standard version of the Smoke Free app recruited over 50,000 people who smoked into an experimental study (Perski et al. 2019a). Benefits of this approach include widespread adoption from the outset, although it does not eliminate the need for dissemination within health care systems and community and public health services. A second approach, advocated within the DTx Real-World Evidence Framework (Kim et al. 2022a), involves designing the mHealth intervention directly within health care systems or community organizations and having researchers from other sectors (e.g., academia, start-ups) supporting, but not necessarily leading, the mHealth intervention development, optimization, and evaluation process. A third approach, which is currently being trialed in Germany as part of the Digital Healthcare Act (Fed. Inst. Drugs Med. Devices 2023), falls within the scope of regulation. Here, approved or vetted mHealth interventions (which need to demonstrate preliminary evidence of effectiveness) can be prescribed directly by health care providers (e.g., physicians, nurse practitioners, pharmacists) (Khadjesari et al. 2021). Research is needed to evaluate the pros and cons of different approaches to scaling and dissemination of evidence-based mHealth interventions, including any unintended harm.

DEVELOPING AND OPTIMIZING MOBILE HEALTH INTERVENTIONS

In this section we discuss exciting opportunities and novel methods that can be employed to develop and optimize mHealth designs in general and JITAIs in particular.

User-Centered Design

UCD is an approach that prioritizes the needs, preferences, and experiences of end users throughout the design and development process (Farao et al. 2020). UCD typically involves several stages. The first stage is user research and needs assessment, in which qualitative and quantitative research are used to understand users' needs, goals, and behaviors (Molina-Recio et al. 2020). Then prototyping and iterative design begins, in which prototypes of the intervention, such as wireframes or mockups, are used to gather feedback from users and the design is refined based on user input. Afterward, codesign/participatory design is initiated, in which end users are active participants in the design process. The app is then evaluated for usability with representative users to gather feedback on the user experience and make iterative improvements. Mechanisms for ongoing user feedback and engagement are established after the intervention is deployed (McCurdie et al. 2012). The

UCD approach may be especially beneficial if the target population is known to have low adherence to mobile interventions or experience usability barriers to mHealth interventions such as low levels of educational attainment (Vilardaga et al. 2018). Few, if any, studies have examined whether UCD methods in the design of JITAIs actually increase user engagement or improve SUD outcomes.

Latent Class Analysis

Latent class analysis (LCA) is a statistical modeling technique used to identify unobserved or latent subgroups or classes within a population based on observed categorical variables (Collins & Lanza 2009). LCA could be used to identify different substance use profiles based on patterns of substance use, co-occurring disorders, motivations, and other relevant factors. For example, Cleveland et al. (2010) identified six latent classes of substance use among a sample of high school students: nonusers; alcohol experimenters; alcohol, tobacco, and other drug experimenters; people who currently smoke; people who binge drink; and heavy users. This type of information could be used to guide the development of JITAIs that tailor content to the specific needs and challenges for specific subgroups of substance users (Lanza & Rhoades 2013). For instance, LCA could be used to identify subgroups of heavy alcohol users who drink primarily in response to high cravings or high stress or who have different combinations of lapse risk factors. Further, LCA could be used to identify individuals who are more likely to respond to intervention content that is consistent with cognitive behavioral therapy or ACT.

Time-Varying Effect Models

Time-varying effect models (TVEMs) are statistical models used to examine how the relationships between predictor variables and an outcome change over time. For example, multiple studies have identified time-varying relationships between smoking and imminent lapse risk factors such as craving, negative affect, self-efficacy, easy cigarette availability, and other contextual factors (Koslovsky et al. 2018, Lanza et al. 2013). TVEM findings may have important implications for JITAI development. Specifically, TVEM findings may highlight which variables should be intervened upon during specific days or stages of a substance use quit or reduction attempt.

Machine Learning

mHealth interventions collect a wealth of information that can be used to guide and tailor intervention development, including repeated self-report via EMA, passively collected data from sensors, and metadata collected from smartphones (e.g., user engagement, WiFi connection, current battery level, timing and frequency of text messages and phone calls). Given the volume and complexity of these data, machine learning techniques are increasingly being used to build predictive models that estimate an individual's future state or behavior (Abo-Tabik et al. 2021). Machine learning techniques offer several advantages in predicting dynamic health behaviors. First, they excel in efficiently handling the substantial volume of continuous and multifaceted data produced by mobile technology, including both real-time sensor and EMA data (Timms et al. 2014). Second, machine learning facilitates exploratory analysis by identifying variables that are pertinent to outcome prediction, enabling the examination of previously unexplored relationships in the literature (Riley et al. 2011). Through feature engineering, wherein raw data are transformed into new, condensed variables to enhance the model (e.g., the variance or change in slope over a 5-minute time period), machine learning facilitates the discovery of significant predictors, such as the duration between substance use occasions and the deviation from an individual's average daily or weekly mood (Hastie et al. 2001). Lastly, machine learning demonstrates adaptability to new data, making

it particularly well suited for modeling intricate and dynamic connections among individual-level characteristics, changing social and environmental factors, and behavioral outcomes over time (Lee & Lee 2020).

Sequential Multiple Assignment Randomized Trial Designs

Sequential multiple assignment randomized trial (SMART) designs (Almirall et al. 2014) have substantial potential for improving outcomes. Traditionally, clinical trials assign each research participant to an intervention group, and each participant remains in that group until the end of the trial. Research has shown that most SUD relapses occur early during quit attempts (Piasecki 2006), and few individuals eventually achieve their substance abstinence/reduction goal following an early relapse (Brandon et al. 2007). This means that participants remain in their assigned treatment group for the entire trial (e.g., 6–12 months) even though they are unlikely to be helped by the assigned intervention after initial relapse. In SMART designs, participants are rerandomized into different treatment groups based on their response to initial treatment. For instance, participants in remote JITAIs could be rerandomized by JITAI software to receive different interventions on the basis of self-reports and/or remotely conducted biochemical tests of abstinence [e.g., remote carbon monoxide (CO) assessment of recent smoking]. Thus, SMARTs may increase desired outcomes (e.g., smoking cessation) by iteratively assigning different treatments to individuals who do not achieve sustained abstinence with their initial intervention assignment and by identifying which treatments are most effective for certain subsets of participants. However, few SMART JITAIs have been developed that can automatically rerandomize participants to various SUD interventions (Nahum-Shani et al. 2022).

Microrandomized Trials

A microrandomized trial (MRT) is an experimental study design that enables the optimization of JITAIs (Klasnja et al. 2015). Unlike a traditional RCT, in which participants are generally randomized to a treatment condition at one point in time, in an MRT, participants are randomly assigned to receive content at multiple decision points over the course of a study. This randomization process allows one to examine the causal effects of the intervention on outcomes while accounting for time-varying factors. In doing so, it becomes possible to answer research questions like what type of intervention message is best suited for different situations. For example, in an MRT examining the Sense2Stop stress-management JITAI for smoking relapse prevention (Battalio et al. 2021), preliminary results demonstrated that stress-management prompts were associated with an increased likelihood of experiencing stress in the subsequent 2 hours compared with situations in which no stress-management prompt was delivered, suggesting that participants may not be receptive to stress-management activities while stressed during a quit attempt (Spring et al. 2023).

NEXT STEPS AND IMPORTANT QUESTIONS THAT NEED TO BE ADDRESSED

In this section, we discuss next steps for the future of mHealth intervention development and important questions and barriers that need to be addressed to realize the full potential of mHealth.

Hybrid Mobile Health Interventions

There is still some skepticism regarding the ability of mHealth interventions to effectively address SUDs, particularly for individuals with complex needs. Although this is a vital question for mHealth research, many individuals with substance use problems (and particularly those from disadvantaged groups) do not have easy or free/affordable access to effective SUD treatments

(Murphy 2022, Panchal et al. 2023, Subst. Abuse Ment. Health Serv. Adm. 2023). Evidence-based mHealth support is arguably better than no support (Kaner et al. 2017), but mHealth treatment failures may also delay or deter individuals from seeking future treatments. Clinicians may seek to avoid such negative outcomes via initial assessment and triage to more intensive interventions for patients who are unlikely to respond to mHealth-only interventions. For instance, if human counseling and pharmacotherapy are available, a screening step might be followed by a recommendation step in which potential interventions are matched to the patient's needs. mHealth interventions can also be used to supplement and extend more traditional counseling interventions to make treatment content available between sessions and/or reduce the volume of counseling that is required.

Conversational Agents

Chatbots/conversational agents are a type of computer software that enables text-based or audiovisual interactions with mHealth users. Chatbots exist in different forms (e.g., structured and unstructured bots) (see Alphonse et al. 2022). Structured bots typically allow the user to select inputs from a list of predefined options, and the bot responds with prewritten messages. Unstructured bots, on the other hand, tend to be underpinned by natural language processing and, more recently, by large language models (e.g., GPT, Replika) that can manage free-text user inputs and use these to generate individualized responses/messages (Kusal et al. 2022). Large language models, which have a degree of randomness built in, increase opportunities for users to perceive messages as personalized and more creative. Chatbots are often designed to have a specific persona or communication style (e.g., funny, empathetic, prescriptive) and thus have the potential to make user interactions feel more personally relevant and engaging (Perski et al. 2017b). Although still in their infancy, a variety of chatbots (e.g., those delivered via embodied “avatars,” those delivered via existing communication and social media services) have recently been developed and evaluated within the smoking cessation domain (He et al. 2023). Meta-analytic findings indicate initial promise in the acceptability and effectiveness of these conversational agents (He et al. 2023).

What Constitutes Success for Mobile Health Interventions?

The efficacy and effectiveness of SUD interventions are traditionally assessed by determining abstinence at the final follow-up visit (e.g., objectively confirmed 7-day self-reported abstinence at 6-month follow-up) (Benowitz et al. 2020). Some have suggested that this methodology is limited, especially in light of the assessment capabilities of smartphone-based EMAs and passive/active sensor data collection. Specifically, since mHealth interventions allow for more granular measures of substance use (e.g., daily, hourly), intervention effectiveness can be assessed at the day/week/month level (e.g., number of days of abstinence, number of days until first or second lapse). Further, EMAs can be used to determine whether interventions influence factors that ultimately reduce the likelihood of lapse/relapse (e.g., does the intervention reduce stress, which reduces the occurrence of lapse/relapse?). Thus, treatment mechanisms can be more accurately measured and intervened upon (Perski et al. 2023). In addition, EMAs allow researchers to determine whether interventions can decouple variables that, when linked, lead to undesired outcomes (e.g., increased negative affect increases smoking urges, and decoupling this relationship could result in fewer smoking lapses) (Benson et al. 2022). A meta-analysis of 126 studies that collected EMA data from substance users showed that, on average, 75% of prompted EMAs were completed (Jones et al. 2019). This level of EMA completion is generally in line with expectations in the field (Shiffman et al. 2008). However, studies that involve EMA data collection with understudied and vulnerable populations (e.g., adults experiencing homelessness) and studies that

use EMA data collection to inform JITAIs over long periods of time (e.g., 6–12 months) may see lower completion rates. There are currently no established benchmarks for the required level of interaction or engagement with mHealth interventions to demonstrate efficacy or effectiveness. Research is needed to generate dose–response curves, especially when uncompensated EMAs are used to drive interactions with and tailoring of intervention content.

Objective Verification of Outcomes

Another burgeoning issue is the limited availability of low-cost devices or methods to remotely and accurately monitor substance use. Several studies have indicated that EMA methods may yield more valid reports of substance use compared with timeline follow-back measures (Mun et al. 2021, Shiffman 2009, Yang et al. 2023). Further, objective verification of self-reported substance use is needed to increase scientific rigor and is recommended whenever feasible in SUD treatment trials due to demand characteristics, errors in memory, and stigma associated with SUDs (Benowitz et al. 2020, Thrul et al. 2023).

Since the COVID-19 pandemic began in 2020, many research studies focusing on substance use and abuse have moved from in-person to remote settings. Governments spend billions of research dollars on the development of new interventions, and objective measures of substance use can offer information about which interventions are effective. Thus, there is a critical need to remotely verify recent substance use (e.g., alcohol, smoking, cannabis). Notably, some types of samples are easier to collect and assess (e.g., breath samples are relatively easy to collect and assess, while blood, tissue, and urine samples are more difficult to collect and evaluate remotely) (Thrul et al. 2023). Currently available high-quality sensors that can detect recent smoking via expired CO levels generally cost \$750–\$1,300 and thus are not practical for remote use. One relatively low-cost CO device, the Bedfont iCO (\$65 per device), is available on the market. The iCO device can be used for multiple CO tests and can be linked with third-party smartphone apps (Tonkin et al. 2023). Resources should be invested in the development of low-cost sensors that can remotely and objectively confirm self-reported substance use.

CONCLUSION

We are in the early stages of a paradigm shift toward the mobile delivery of interventions for SUDs. Never before have there been so many opportunities to tailor novel interventions to the needs of specific individuals in real time and in real-life situations. Through dynamic tailoring, it may be possible to be more responsive to the needs of minoritized people who have been less likely to participate in clinical trials and therefore are frequently offered interventions that do not work very well for them. Unfortunately, nearly all of the mHealth interventions that are available for download today have not been evaluated for efficacy or effectiveness. Thus, individuals are downloading interventions that may not be effective for addressing their problems, which could delay or discourage the use of future well-studied and effective interventions. More needs to be done in the health care community to steer patients away from untested interventions and toward interventions that have been empirically validated.

The iterative process of developing, optimizing, and evaluating mHealth interventions requires multiple skill sets and expertise ranging from public health, medicine, ethics, and behavioral science to user experience and interface design, software engineering, data science, signal processing, and statistics. This is an exciting time for collaborative multidisciplinary teams. mHealth researchers would benefit from intersectoral collaborations with a diverse range of professionals working across public health organizations, community health and faith-based organizations, and small to large enterprises (e.g., start-ups).

On a final note, it is important to consider funding sources for the development of mHealth interventions for SUDs. Once developed, mHealth interventions can be rapidly tested because participation does not necessarily require in-person visits. Thousands of individuals can be recruited from across the country or globe and enrolled in treatment trials in a matter of months. Thus, new funding mechanisms are needed to support shorter-term, higher-budget mHealth trials (e.g., 3-year NIH grants with \$1,000,000 in direct costs per year) that use efficient and innovative designs [e.g., MOST (Multiphase Optimization Strategy) designs, SMART trials] (Almirall et al. 2014). Such funding mechanisms would enable the rapid testing and deployment of effective treatments to those who need them. Furthermore, participant recruitment and management protocols must be developed to ensure that representative samples are being enrolled in mHealth trials and to reduce fraudulent enrollment in paid trials. Finally, it is imperative that modern metrics for mHealth intervention effectiveness are developed and implemented (e.g., objective measurement of substance use).

SUMMARY POINTS

1. Mobile health (mHealth) interventions can use data from mobile devices to actively or passively monitor substance use (e.g., ecological momentary assessment, wearable sensors).
2. A diverse range of smartphone-app-based interventions for substance use disorders (SUDs) have been developed, although very few have been evaluated for efficacy or effectiveness.
3. Just-in-time adaptive interventions (JITAI) are automated, smartphone-based interventions that aim to provide tailored support in moments of vulnerability and receptivity.
4. Mobile interventions may increase the reach of SUD interventions and reduce the burden associated with in-person interventions.
5. mHealth interventions have been developed for multiple SUDs, including tobacco, cannabis, alcohol, and other illicit substances.
6. Special considerations may be needed when developing mHealth interventions for underserved and vulnerable populations. Targeted mobile interventions for SUDs have been developed for socioeconomically disadvantaged populations, racial/ethnic minority populations, and individuals with minoritized sexual orientation/gender identities, among others.
7. Development of a JITAI involves a multistep process to identify key predictors of substance use, develop a parsimonious model, and create tailored intervention content.
8. Emerging strategies for the development and optimization of mHealth interventions include user-centered design, statistical methodologies such as latent class analysis and time-varying effect models, machine learning, and evolving trial designs such as sequential multiple assignment randomized trial (SMART) designs and microrandomized trials.
9. Next steps for mHealth interventions for SUDs involve addressing challenges with engagement, hybrid intervention designs, the use of conversational agents/artificial intelligence, and objective verification of outcomes.

DISCLOSURE STATEMENT

M.S.B. and D.E.K. are inventors of the Insight mHealth Platform™, which can be used to develop smartphone applications for ecological momentary assessment and just-in-time adaptive interventions. They receive royalties from the University of Oklahoma Health Sciences Center when individuals outside of the institution use this platform to create and deploy research studies. M.S.B. and D.E.K. have also received grant funding from the National Institutes of Health. D.E.K. previously received varenicline at no cost from Pfizer Inc. for an investigator-initiated trial. O.P. is an unpaid scientific advisor to the Smoke Free app.

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