



Wearable and Wireless mHealth Technologies for Substance Use Disorder

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Abstract

Purpose of Review The goal of this scoping review is to evaluate the advances in wearable and other wireless mobile health (mHealth) technologies in the treatment of substance use disorders.

Recent Findings There are a variety of wireless technologies under investigation for the treatment of substance use disorder. Wearable sensors are the most commonly used technology. They can be used to decrease heavy substance use, mitigate factors related to relapse, and monitor for overdose. New technologies pose distinct advantages over traditional therapies by increasing geographic availability and continuously providing feedback and monitoring while remaining relatively non-invasive.

Summary Wearable and novel technologies are important to the evolving landscape of substance use treatment. As technologies continue to develop and show efficacy, they should be incorporated into multifactorial treatment plans.

Keywords Wearable sensor · Biosensor · mHealth · Substance use disorder

Introduction

Substance use disorder (SUD) is a leading cause of global morbidity and mortality. In 2018, approximately 20.3 million people in the USA reported having a SUD over the past year [1]. Over 67 thousand overdose-related deaths occurred nationwide in 2018, with roughly 128 people dying from an opioid overdose [2]. World Health Organization statistics implicate problematic alcohol consumption in three million deaths worldwide in 2016 alone [3]. In addition to increasing an individual's mortality risk, substance use is associated with increased transmission of infectious diseases such as HIV, hepatitis B, and hepatitis C [1].

The search for more efficacious treatment options for people who use drugs (PWUD) is increasingly important, as the prevalence and associated morbidity of SUD are climbing, and current treatment options are limited. A mere 8.1% of people with SUD in the USA receive treatment, which often

consists of a combination of medication and in-person programs at a rehabilitation center [4]. Financial and geographic barriers to access are common and contribute to this poor level of treatment access. While there are some medication-based options to help treat SUD, they are associated with several limitations and are most successful when combined with other forms of treatment options [5].

Digital diagnostics and therapeutics are emerging fields for the treatment of SUD, paralleling the rise of mobile technology use in society. Studies have found that approximately 82–95% of people presenting to the emergency department have a cellphone, with the majority of those being smartphones with internet capability [6–8]. The ability to reach millions of people rapidly and asynchronously creates unique opportunities for healthcare prevention, intervention, and treatment in ways that were previously unattainable.

Mobile health (mHealth) is the field that incorporates mobile technologies into the practice of healthcare [9]. This is unique from web- or computer-based devices which are categorized under the broader field of “eHealth,” which refers to the use of electronic technologies for healthcare [10]. mHealth technologies are inclusive of mobile phone-based devices, such as applications, as well as wireless technologies, such as wearable devices that are directly worn by the patient and continuously measure physiologic or behavioral parameters. There are many modalities that can be used in mHealth in

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order to accomplish this goal. As technology is rapidly evolving, it is important to continually evaluate new modalities being used to treat people with SUD. Toward this goal, the current manuscript reviews the literature from the past 5 years to understand and evaluate the current landscape of wearable and novel technology-based sensors for the treatment of SUD and problematic substance use.

Search Methods

A scoping review of the literature was performed with the assistance of a research librarian. Three databases (PubMed, Scopus, and IEEE) were queried for articles that included the use of wearable devices or mHealth in the treatment of SUD. The following search strategy was used:

“Wearable technology” OR “wearable sensor” OR “wearable device” OR “Wearable Electronic Devices” [mesh] OR Wearables OR “Mobile devices” OR mHealth OR “Contactless monitors” OR Ingestible OR Biosensor OR “Blue tooth” OR radar OR “ambulatory monitoring” OR “Telemedicine” [mesh]
AND
(Heroin OR Cocaine OR Methamphetamine [mesh] OR Cannabis [mesh] OR Alcohol OR Opioid OR Marijuana OR Sedative OR “Benzodiazepines” [mesh] OR Opiates OR “Analgesics, Opioid” [mesh])
AND
(treatment OR “Harm Reduction” [mesh] OR “harm reduction”)

The initial search yielded 1124 articles (Fig. 1). Articles were included for review if they were performed from January 2015 to present, fit the search criteria, or were independently found to meet inclusion criteria (reviewed a wearable or other wireless technology used for the treatment of a substance use disorder), resulting in 28 articles (Table 1). Harm reduction was specifically included in the search terms to capture studies that focus on all possible stages of treatment. Articles were then analyzed by two independent reviewers and categorized based on the type of substance use being treated. Studies that focused exclusively on mobile phone applications or web-based interventions were excluded, as these topics have extensively been reviewed in the recent literature [4, 11–13]. Studies that focused solely on tobacco were also excluded as the treatment modalities for tobacco use disorder often differ from that of other substances of abuse. Articles fell into four major categories: alcohol use disorder (AUD), cocaine use disorder, opioid use disorder (OUD), or general SUD.

Treatment of Alcohol Use Disorder

Wearable devices, such as transdermal alcohol sensors or mobile phone-linked breathalyzers, can objectively measure alcohol use while remaining minimally invasive. Transdermal sensors are currently employed in the healthcare and criminal justice systems to detect alcohol use. These devices continuously and passively measure the transdermal alcohol content (TAC) of the wearer’s sweat, allowing for alcohol consumption to be detected. Additionally, the severity of consumption for a given day can be classified by estimating breath alcohol content from peak TAC readings and time-to-peak TAC [14]. A commonly used transdermal alcohol sensor is the Secure Continuous Alcohol Monitoring (SCRAM) system (Alcohol Monitoring Systems, Inc.), which is secured to the wearer’s ankle and measures TAC every 30 min during wear. SCRAM has been well studied in alcohol-consuming populations, particularly in the context of contingency management (CM) therapies for AUD. Many CM programs rely on self-reporting, urinalysis, and/or breathalyzer tests to determine compliance, but these methods have limited accuracy [15]. Dougherty et al. utilized the SCRAM device as an objective measure to determine the efficacy of CM in non-treatment-seeking heavy drinkers and found that TAC-based CM is capable of lowering patterns of heavy alcohol consumption [14].

Additionally, TAC devices are utilized by the judicial system to determine if a defendant is adhering to court-ordered abstinence from alcohol use. Mathias et al. used SCRAM to study current CM protocols in defendants arrested for driving while intoxicated (DWI) [16]. The authors concluded that TAC-informed CM may be used to increase compliance for court-ordered alcohol abstinence in DWI defendants during the pretrial phase. While they minimize the burden to the wearer, transdermal sensors have limitations; they may be uncomfortable, can lead to social stigma, and lack sensitivity for detecting small amounts of alcohol consumption.

Mobile phone-linked breathalyzer technology has also been demonstrated to improve outcomes for AUD treatment programs. Triple A, SoberDiary, and SoberLink are examples of mHealth systems that pair a portable Bluetooth breathalyzer with a mobile phone, allowing users to transmit breath alcohol measurements that can be extrapolated to estimate blood alcohol content. These systems use facial recognition software or camera recordings to confirm the identity of the user during the test and are capable of sending real-time communications between the user and the administrator. Studies have found the technology to be useful for tracking AUD treatment progress and permitting early recognition of relapse to alcohol use [17, 18]. Patterns of fewer missed tests and increased compliance correlated to favorable AUD treatment outcomes [17, 19]. Additionally, mobile phone-linked breathalyzers may increase mindfulness surrounding the level of alcohol consumption in many individuals, promoting safer alcohol consumption practices [20•]. While qualitative interviews regarding

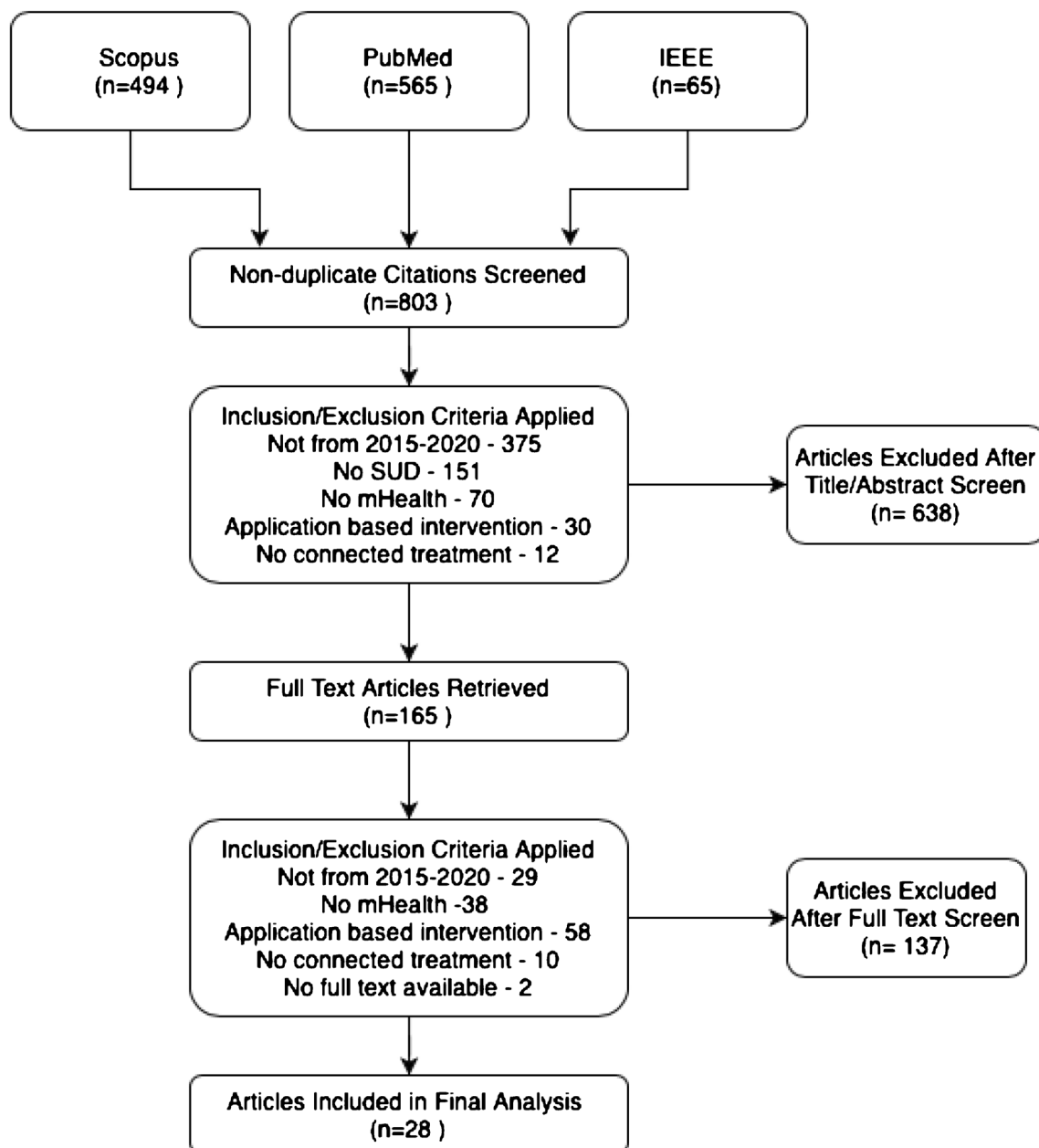


Fig. 1 PRISMA flow diagram

breathalyzer technology showed that participants generally had a positive view of the technology, they also noted that there is a learning curve to be able to operate the device and thus would prefer more training prior to using it [20•].

Advancements in wearable electrodermal activity (EDA) sensors have also enabled the development of novel AUD treatment methods. Leonard et al. deployed the Empatica E4 biosensor in ten non-treatment-seeking college undergraduate females with scores three or higher on the Alcohol Use Disorder Identification Test-Consumption (AUDIT-C) to measure changes in EDA associated with feelings of craving and stress [21]. When a change in EDA was identified, the application provided users with cognitive behavioral therapy–

themed questions and strategies if the users confirmed it was a negative emotional trigger. Seven of the ten participants reported that the system was either “somewhat” or “very” effective in reducing alcohol consumption.

Treatment of Cocaine Use Disorder

Cocaine use results in an abrupt catecholamine surge leading to sympathetic nervous system excitability that produces the desired euphoria but also causes sweating, increased heart rate, constriction of peripheral blood vessels, and distinct body movements. Recent mHealth research efforts relating to cocaine use disorder

Table 1 Select wearable and wireless mHealth studies for substance use disorder

First author	Date	Text reference	Study type	Modality	Device	Summary
Alcohol use disorders						
Dougherty	2015	14	Non-randomized trial	Wearable	Transdermal alcohol sensor (SCRAM II)	Accurately measured TAC to report if a drinking event occurred and the severity of the drinking (none, low, moderate, heavy). In combination with contingency program, decreased heavy drinking
Barnett	2017	15	RCT	Wearable	Transdermal alcohol sensors (SCRAM II and SCRAMx)	30 non-treatment-seeking, heavy drinkers were randomized into contingent reinforcement and non-contingent reinforcement groups. Drinking episodes were detected by SCRAM based off of a participant's TAC. The use of SCRAM in this study allowed for uninterrupted monitoring of alcohol use and limited interference with the participants' daily life
Mathias	2018	16	Non-randomized trial	Wearable	Transdermal alcohol sensor (SCRAM)	SCRAM was used for monitoring alcohol intake for adults arrested with DWI and classified as heavy drinkers. TAC was monitored using SCRAM in combination with a contingency management program
Hamalainen	2018	17	RCT	Mobile phone-linked breathalyzer	Triple A	Healthcare providers used the system to schedule a participant breathalyzer test. Of the 10,973 scheduled tests, 7743 were completed (70.1%). The breathalyzer eHealth system (Bluetooth breathalyzer + mobile app) was useful for monitoring AUD treatment and assisted clinicians in identifying relapse. A correlation was found between patterns of missed tests and the onset of drinking
Gordon	2017	18	Review	Mobile phone-linked breathalyzer	SoberLink	SoberLink recognizes two standard drinks for 2–5 h after use or heavy alcohol use up to 12 h post consumption. Users operate the breathalyzer 2–4 times a day. Facial recognition confirms patient identity. Notifications are sent to the clinician if tests are missed, failed facial recognition, or any tampering
You	2017	19	Non-randomized trial	Mobile phone-linked breathalyzer	SoberDiary	Increased compliance with SoberDiary was associated with better treatment outcomes including drinking frequency, amount of alcohol consumed, and completely abstaining from alcohol use
Lauckner	2019	20	Non-randomized trial	Mobile phone-linked breathalyzer	BACTrack Mobile Pro	80% of the participants reported the technology to be useful because it made them consider drinking less often and made them mindful of how much alcohol they were consuming
Leonard	2017	21	Non-randomized trial	Wearable	Empatica E4	70% of participants reported that the system (wearable sensor to detect changes in skin conductance + mobile phone-based CBT) was either “somewhat” or “very” effective in reducing alcohol consumption
Cocaine use disorders						
Carreiro	2015	23	Observational	Wearable	Affectiva Q sensor	Wearable sensor (measuring EDA, skin temperature, and motion) detected cocaine use events captured on urine drug screen, self-report, or both. Participants (<i>N</i> = 15) reported overall positive experience with the biosensor
Holtyn	2019	24	Observational	Wearable	MotionSenseHRV	Proposed development of an improved wrist-worn sensor suite, incorporating lessons learned from deployment of the chest band-based AutoSense wearable sensor suite

Table 1 (continued)

First author	Date	Text reference	Study type	Modality	Device	Summary
Opioid use disorders						
Chai	2017	26	Non-randomized trial	Digital pill		Digital pills containing oxycodone given to 10 participants in the ED and outpatient setting. The system was feasible to determine opioid ingestion. 80% found the pills acceptable and 90% were willing to continue use
Chai	2017	27	Non-randomized trial	Digital pill		Oxycodone was formulated into a digital pill, and 16 participants ingested them “as needed” for outpatient pain management with 84% accuracy
Carreiro	2015	28	Observational	Wearable	Affectiva Q sensor	Pilot study of $N=4$ participants receiving intravenous opioids in a hospital setting; increase in EDA corresponded to opioid administration
Carreiro	2016	29	Observational	Wearable	Affectiva Q sensor	Measured changes in skin temperature, EDA, and locomotion in 30 participants receiving intravenous opioids in the hospital setting. Significant increase in skin temp and decrease in motion associated with opioid administration. Biometric changes varied based on opioid use history
Mahmud	2018	30	Observational	Wearable	Affectiva Q sensor	Machine learning algorithms applied to wearable sensor data from 30 hospitalized individuals able to detect opioid use with up to 99% accuracy
Rumbut	2019	31	Observational	Wearable	Empatica E4	Machine learning applied to data collected of three individuals using kratom in natural settings able to correctly identify kratom use with 95% accuracy
Nandakumar	2019	32	Non-randomized trial	Mobile phone	NR	Contactless sensor system converted mobile phone into sonar device to monitor respiratory rate and movement to detect opioid overdose; in 209 participants, the system detected opioid-induced respiratory depression with 87% sensitivity and 89% specificity
Chintha	2018	33	Observational	Wearable	Empatica E4	Wearable sensors were used to detect recurrent opioid toxicity after 11 participants received the opioid antagonist naloxone for an opioid overdose; 90 min after naloxone administration, significant changes were noted in heart rate and skin temperature
Dhowan	2019	34	Animal model	Subcutaneous drug delivery device	A2D2	Wearable closed-loop antidote delivery device that injects naloxone subcutaneously after being activated by an external magnetic field; tested in mice which demonstrated ability to rapidly release naloxone after evaluation
Ahamad	2019	35	Survey	Wearable	NR	Of 1061 persons who use drugs that were surveyed about willingness to use a wearable overdose detection device, 54% were willing to wear such a device; people who had overdosed in the past, were on methadone, and had a history of chronic pain were more likely to be accepting
Miranda	2018	36	Non-randomized trial	Percutaneous electrical nerve stimulator	BRIDGE	Percutaneous nerve stimulation was delivered with a portable device to 73 participants who were undergoing opioid withdrawal induction; there was a significant decrease in withdrawal symptoms after the device was applied
General substance use disorders						
Kennedy	2015	22	Non-randomized trial	Wearable	AutoSense	In 40 polysubstance users undergoing MAT, the device detected the heart rate and showed predictable changes during cocaine use, heroin use, cocaine or heroin craving, and stress. The device was deemed highly acceptable overall, but a third of

Table 1 (continued)

First author	Date	Text reference	Study type	Modality	Device	Summary
Carreiro	2020	25	Mixed methods	Wearable	Empatica E4	participants noted it was uncomfortable and felt self-conscious while wearing it In 30 individuals in treatment for SUD, a wearable sensor was able to detect stress events based solely on accelerometry data with 74.5% accuracy, craving with 75.7% accuracy, and craving vs. stress with 76.8% accuracy. The addition of EDA and heart rate measurements resulted in increased accuracy. Participants had a positive experience and were accepting of using the wearable sensor
Future implications						
Metcalf	2018	37	Summative study	Augmented reality	Kinect	Preliminary study of an augmented reality game allowing people with AUD to counter substance use cues through active movements such as punching and kicking
van Heerden	2017	38	Review	Virtual reality	Multiple	A review describing new interdisciplinary approaches to alcohol and HIV research
Pandey	2019	38	Review	Transdermal biosensors and drug delivery devices	Multiple	A review of recent advances in transdermal biosensing and drug delivery
Portelli	2017	40	Methods paper	Wearable	Custom developed	A description of the design and testing of a non-contact electrode used to sense biopotential signals
Tofighi	2018	41	Review	Digital interventions for substance use	Mobile phones	Review of mobile phone- and web-based interventions for individuals with SUD and discussion of the utility of these in providing primary care providers passively collected data streams that can be used to automatically provide feedback to providers and the at-risk individuals

RCT randomized controlled trial, *NR* not reported, *TAC* transdermal alcohol content, *SUD* substance use disorder, *CBT* cognitive behavioral therapy, *DWI* driving while intoxicated, *EDA* electrodermal activity, *AUD* alcohol use disorder, *ED* emergency department

focus on the use of wearable biosensors to improve understanding of physiological biomarkers of stress, craving, and drug use, with the goal of real-time identification and mitigation of risk factors or precipitants for return to cocaine use.

Kennedy et al. demonstrated the ability of the chest band-mounted AutoSense device to capture robust heart rate data from drug users undergoing outpatient treatment for OUD and used these data to identify episodes of cocaine use, opioid use, and mental states of interest such as stress and craving (also see “General Treatment of Substance Use Disorder” below) [22]. Carreiro et al. utilized the Affectiva Q sensor to demonstrate the feasibility of using a compact wrist-mounted sensor suite to detect cocaine use events in a real-world setting based on changes in EDA, skin temperature, and locomotion, including suspected episodes that were not captured by self-report or urine drug screening [23].

Interestingly, although Kennedy et al. report that AutoSense was generally acceptable to participants, nearly a third of participants rated the device as uncomfortable and more than a third of participants reported feeling self-conscious while using the device [22]. Holtyn et al. are developing a wrist-worn sensor suite

dubbed MotionSenseHRV to address wearability and reliability shortcomings they have identified with AutoSense. The ultimate goal of pinpointing the exact timing of cocaine use in natural settings can be used to develop individualized risk profiles for return to cocaine use and to prompt self-report of contextual information regarding potential triggering situations or circumstances [24]. Evidence to promote this potential use is provided by a recent study of individuals in recovery from SUD [25•]. Participants in recovery were not only willing to engage with wearable sensing technology but also felt “connected” by wearing the sensor, were more mindful of their emotions while wearing the sensor, and looked forward to the possibility that it could be used to summon help from a clinician or member of their peer support system in the future.

Treatment of Opioid Use Disorder and Related Conditions

OUD encompasses a broad spectrum of disease and provides many opportunities for device-based intervention strategies,

the most basic of which is the detection of opioid use. Chai et al. described the use of a digital pill to detect opioid ingestion, both in and out of the hospital setting [26, 27]. The digital pill is a gelatinous capsule containing a radiofrequency emitter that encloses an opioid tablet. The pill is activated by the chloride ion gradient in the stomach and sends a signal to an external radar to confirm ingestion. In two studies, the accuracy of digital pills to detect oxycodone ingestion was noted to be 85% and 87% [26, 27]. Wearable sensors have also been used in various populations to detect episodes of opioid use. Carreiro et al. described the use of a wrist-mounted sensor (Affectiva Q sensor) that measured EDA, accelerometry, and skin temperature to detect opioid injection in the hospital setting [28–30]. Using a similar wrist-mounted sensor (Empatica E4), Rumbut et al. described the detection of the opioid-like drug kratom in community users with 95% accuracy [31].

Correctly identifying opioid effects with a sensor may be valuable for monitoring that drug use has occurred; however, the ability to further detect opioid toxicity and overdose would provide a crucial opportunity for intervention in this population. Toward this goal, Nandakumar et al. described detection of opioid toxicity using a mobile phone [32]. This contactless sensor system used the mobile phone's speaker and microphone as a short-range sonar system to detect decreases in respiratory rate and movement that correspond to an opioid overdose. The system was tested in hospitalized surgical patients and in opioid users in a supervised injection facility and detected opioid-induced respiratory depression with 87% sensitivity and 89% specificity. Chintha et al. described the use of a wearable wrist sensor (Empatica E4) to detect recurrent opioid toxicity after treatment for an opioid overdose, suggesting a role for wearables in post-overdose monitoring [33].

Automated detection of opioid overdose naturally leads to the concept of automated intervention. Although not widely available, this is an area of active research. Dhowan et al. described a prototype of a closed-loop antidote delivery system to inject naloxone upon opioid overdose detection, which was tested in an animal model [34]. With any such devices, however, significant concerns exist regarding the likelihood of acceptance by the target population. Ahamad et al. have explored factors associated with acceptance of an overdose detection device; only half of the respondents were accepting of the concept, but certain individual characteristics were associated with increased likelihood of acceptance (history of overdose in the past, being on methadone maintenance therapy, and a history of chronic pain) [35].

On the opposite end of the spectrum, lack of opioids can have detrimental consequences in an individual with OUD and provides yet another opportunity for digital intervention. Opioid withdrawal causes physical distress, is a trigger for return to use, increases risk of overdose, and signifies an

important point for intervention. Miranda and Taca described a percutaneous neurostimulation device to treat symptoms of opioid withdrawal [36]. Our search did not yield results related to devices to detect withdrawal, although the characteristic changes in physiology would make it an excellent candidate for wearable-based detection.

General Treatment of Substance Use Disorders

While digital technologies often target a specific SUD, some aim for broad-spectrum applicability, focusing on general factors that affect PWUD. A common focus is detecting episodes of stress and/or craving. Times of craving and stress are high risk for the potential for relapse, and known physiologic correlates (particularly for stress) make this an area of interest. For example, an increased heart rate has been shown to be associated with craving for cocaine and heroin and periods of stress in people with polysubstance use [22]. The ability to objectively detect stress or craving provides a time period where providing an intervention may help prevent the relapse from occurring.

While many wearable devices have a multitude of sensors, including electrocardiogram leads, accelerometers, and galvanic skin response sensors, Carreiro et al. utilized the wrist-mounted Empatica E4 to demonstrate that accelerometry alone detected 74–77% of episodes of stress and drug craving among individuals with SUD [25]. The addition of EDA and heart rate measurements resulted in a modest improvement in detection rate to 80–82%. This is an important finding because, while attaining perfect sensitivity and specificity is attractive from an academic perspective, real-world limitations on hardware (e.g., size, battery life) will likely mandate that a “good enough” approach be adopted: a biosensor fails to detect all of the events that occur when it is not worn or when its battery is depleted. In the same study, individuals in recovery from SUD preferred a wearable sensing device if it has a streamlined and esthetically appealing form factor and incorporates functions that serve other functions in daily life, such as telling time and fitness tracking. Thus, a wearable biosensor suite that is packaged in an attractive yet functional form factor with the capability to provide real-time notifications to the wearer, their clinician, and/or their support network of stress, craving, and drug use events holds promise as a vehicle for delivering targeted real-time behavioral interventions for SUD.

Future Research Implications in mHealth

There are multiple new or developing wearable technologies that may eventually prove to be effective in the treatment of

SUD. For example, augmented reality and virtual reality have both experienced rapid development and improved consumer accessibility in recent years. Metcalf et al. have suggested a role for these modalities as adjuncts to standard treatment, and van Heerden et al. described a role for virtual reality as a way to screen for heavy alcohol use and provide brief interventions in the treatment setting by accurately assessing how much alcohol a person would typically consume [37, 38].

Whereas the majority of devices available today focus on non-invasive measurement of physical parameters such as heart rate, movement, and temperature, advances in technology are making minimally invasive transdermal molecular sensors and drug delivery systems more common [39]. As sensors and signal processing methods become more sophisticated, contactless devices integrated into clothing may also see broad applicability in the monitoring and treatment of SUD [40]. We anticipate that, as these technologies become more pervasive, increased availability of personalized data will allow for clinicians to more easily design customized treatment plans and provide just-in-time interventions for patients who are at risk of relapse [41].

Benefits of mHealth Modalities in the Treatment of Substance Use Disorder

mHealth technologies offer several advantages compared with traditional modalities. Wearable devices can objectively measure drug use and associated events while remaining minimally invasive. They are often small and look similar to objects that would normally be worn, such as a wristwatch or activity tracker. This limits stigmatization that can be associated with drug use monitoring and treatment. Many of these devices offer continuous data collection capabilities. The continuous nature allows observations to be made while limiting direct observer bias; however, wearing the device itself may affect a person's behavior. Some also have geolocation capabilities that can help determine if a person is in an area where they may be triggered to relapse or can quickly locate a person in case of overdose.

Additionally, many of the parameters that are detected are physiologic data a person would otherwise be unaware of, such as heart rate, EDA, and motion. These parameters can be indicative of a high-risk period for relapse, such as occurs when a person is experiencing stress or drug craving. Changes in such parameters may be detectable before a person is even consciously aware of the risk state, allowing for early intervention. Such just-in-time interventions have the potential to significantly improve adherence to a personalized treatment plan.

Limitations in the Use of mHealth for the Treatment of Substance Use Disorders

One of the most challenging aspects of mHealth is the pace of change in the field. Digital technology advances at an extremely rapid rate compared with more traditional diagnostic and treatment paradigms. Therefore, the studies that validate these devices also need to occur at a similar speed. Performing methodologically sound research can often be time-consuming. Investigators need to balance the need for high-quality research to determine the accuracy of these new technologies with the need for rapid dissemination of results to prevent the technology in question from becoming obsolete before it has been validated.

Although overall smartphone ownership is high, underserved populations, such as those with socioeconomic hardships, may not have the same access to these technologies. However, compared with traditional treatment modalities, the cost associated with wearable technologies is generally lower. Additionally, these devices are currently being used in a clinical setting where the device is provided to the patient. As wearables and other wireless devices are integrated into care, cost and access must be factored into successful implementation.

Another concern is the ability to protect patient privacy. Many mHealth modalities use internet connections or Bluetooth pairing to a mobile device to collect data. In order to protect patients from unintentional breaches of confidentiality, many programs store the data in private databases that are encrypted. Other interventions anonymize responses or avoid making specific references to drugs of abuse to further protect patient privacy [42]. However, as this is a relatively young field, attention to privacy will be of paramount importance as new modalities are put into practice, especially when dealing with sensitive health information.

In contrast to more traditional treatment approaches which are often clinician driven, implementation of mHealth requires an integrated interprofessional team. There are often engineers, computer scientists, and clinicians involved in the process of creating and validating mHealth devices. Despite this potential barrier, there have been many teams that have been successful in working together toward the goal of finding novel treatments given the large impact of SUD. Additionally, the success of mHealth interventions relies heavily on patient acceptance for them to actually be used in practice. Studies among PWUD have shown that they are generally accepting of using wearable and electronic devices [25•, 35•].

Conclusion

mHealth is an important and evolving field in the treatment of SUD. The most commonly used wireless devices

are wearables that use either physiologic monitoring or transdermal drug concentration to detect drug use. In addition, these technologies can decrease heavy use, detect periods of stress and craving to mitigate relapse, and monitor for overdose. Wearable technologies can increase the availability of treatment to people regardless of geographic location and overcome many of the limitations of current treatment options. While numerous studies have demonstrated the ability of these technologies to accurately detect events of interest, there is a paucity of data on the impact of these mHealth modalities on SUD treatment efficacy. Although the current data is promising, future research should focus on the optimal integration of mHealth modalities into evidence-based treatment plans to provide real-time interventions.

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Compliance with Ethical Standards

Conflict of Interest JL reports grants from Alkermes, outside the submitted work. SC reports grant funding by the National Institute on Drug Abuse (K23DA045242 and R44 DA046151). EL, CG, and MN declare no conflicts of interest.

Human and Animal Rights and Informed Consent All reported studies/experiments with human or animal subjects performed by the authors have been previously published and complied with all applicable ethical standards (including the Helsinki declaration and its amendments, institutional/national research committee standards, and international/national/institutional guidelines).

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- Of major importance

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