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esdi[1]Current Reporting of Usability and Impact of mHealth Interventions for Substance Use Disorder: A Systematic Review

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Abstract

Background: Connected interventions use data collected through mobile/wearable devices to trigger real-time interventions and have great potential to improve treatment for substance use disorder (SUD). This review aims to describe the current landscape, effectiveness and usability of connected interventions for SUD.

Methods: A systematic review was conducted to identify articles evaluating connected health interventions for SUD in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Three databases (PubMed, IEEE, and Scopus) were searched over a five-year period. Included articles described a connected health intervention targeting SUD and provided outcomes data. Data were extracted using a standardized reporting tool.

Results: A total of 1676 unique articles were identified during the initial search, with 32 articles included in the final analysis. Seven articles of the 32 were derived from two large studies. The most commonly studied SUD was alcohol use disorder. Sixteen articles reported at least one statistically significant result with respect to reduced craving and/or substance use. The majority of articles used ecological momentary assessment to trigger interventions, while four used biologic/physiologic data. Two articles used a wearable device. Common intervention types included craving management, coping assistance, and tailored feedback. Twenty-three articles measured usability factors, and acceptability was generally reported as high.

Conclusion: Identified themes included a focus on AUD, use of smart phones, use of EMA for intervention delivery, positive effects on SUD related outcomes, and overall high acceptability.

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Contributors: Dr. Carreiro, Dr. Boudreaux and Dr. Amante conceptualized the study. Dr. Carreiro performed the original literature search. Dr. Newcomb, Ms. Leach, and Mr. Ostrowski abstracted data from the included study articles, and Dr. Carreiro resolved all conflicts in the data abstraction process. Dr. Carreiro, Dr. Newcomb, Ms. Leach, and Mr. Ostrowski synthesized and analyzed the data. All authors contributed significantly to the compilation of results and the synthesis of the manuscript.

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Wearables that directly monitor biologic data and predictive analytics using integrated data streams represent understudied opportunities for new research.

Keywords

mHealth; connected health; substance use disorder; intervention; sensors

1. Introduction

Substance use disorder (SUD) is a major public health issue in the United States. In 2014, the Substance Abuse and Mental Health Services Administration (SAMHSA) estimated that 20.2 million Americans (or 8.4% of the total population) met diagnostic criteria for SUD including 16.3 million with alcohol use disorder (AUD) and 6.2 million with an illicit SUD (Lipari and Van Horn, 2013). This highly prevalent group of disorders creates undeniable economic, emotional, and social burdens on the affected and those in their lives. Various evidence-based treatment modalities are available for SUD, including pharmacologic and behavioral-based therapies, but these traditional methods suffer from high failure rates for several reasons (Office of National Drug Control Policy, 2020; Ray et al., 2020). One major factor is the chronic nature of SUD and the need for ongoing treatment as opposed to short term acute care programs. Another key factor is that return to drug use can be precipitated by physical/psychosocial stress, context cues associated with substance use, or other external influences, making it challenging to tailor treatment to individual needs (Clarke et al., 2020; Restrepo-Guzman et al., 2020). Finally, treatment success is frequently limited by accessibility issues-difficulty with initial and/or ongoing access to treatment is a major barrier in this population (Office of National Drug Control Policy, 2020).

Mobile health (mHealth), defined as the use of mobile and wireless devices to deliver healthcare (Park, 2016), is a burgeoning field that has not yet reached its potential for supporting treatment of a variety of health conditions. The related notion of connected health is a conceptual model where wireless and mobile technologies are used to deliver proactive and personalized healthcare (Caulfield and Donnelly, 2013). mHealth approaches provide an attractive option to increase access to and efficacy of SUD treatment. This is due to both the ubiquity of mobile devices as well as other potential benefits of mHealth that can be combined to promote self-efficacy, such as low cost, anonymity, and customizability (Olff, 2015; Tai and Volkow, 2013; Wang et al., 2018). As a result of its unique approach to care, mHealth may engage individuals that are unable or unwilling to engage in traditional treatment modalities due to access barriers, cost, or fear of associated stigma. mHealth tools may also be used as adjunct treatments to individuals in more traditional care models. mHealth modalities can serve as tools both to collect data and deliver interventions. This powerful combination allows for customization of interventions to provide them just-in-time and just-in-space - when and where individuals need them most (Nahum-Shani et al., 2017). This is especially applicable for SUD, as affected individuals are prone to relapse without significant advanced warning that could be detected by routine clinical care.

Of particular interest among mHealh interventions are interventions that react in real time to the needs of the user. Static interventions collect data from the individual (e.g., biologic or physiologic data, self-reported data (EMA), or geolocation) but do not provide dynamic feedback, rather use collected data after the fact to alter the treatment plan. Reactive interventions, in contrast, collect data to provide customized responses to user input in real time. These reactive interventions are termed connected interventions for the purpose of this review, and are of particular interest for SUD treatment. Connected interventions are of special interest as they lay the groundwork for personalized evaluation and treatment in the SUD space. Sensors, mobile phones, and other connected devices can be used to rapidly ascertain multimodal data streams of key importance to SUD. Specifically, many of the constructs in the National Institute of Mental Health's Research Domain Criteria (RDoC) framework, which are recognized as key factors in progress of mental illnesses such as SUDs, can be measured *and intervened upon* via mHealth devices (Torous et al., 2017). This presents unique opportunities for understanding dynamic factors that impact SUD recovery (or progression) in situ, and tailoring treatment to the individual and circumstance.

In just the past three years, multiple reviews have sought to characterize the impact of mHealth on SUD management. A systematic review by Wang et al of mobile apps to monitor and manage mental health disorders (including SUDs) suggested that although promising in the treatment of mental health disorders, many apps lack evidence of efficacy (Wang et al., 2018). Nevag et al performed a systematic review to evaluate digital interventions for SUD recovery, and found that most studies supported feasibility but lacked consistent evidence for effectiveness in this context (Nesvag and McKay, 2018). Finally, Toflgi et al performed a narrative review of various computer, web, and mobile-based interventions for SUD in the primary care setting and concluded that despite the tremendous potential of technology-based interventions, better research is needed for implementation, adoption, and integration into primary care models (Tofighi et al., 2018).

Despite these recent comprehensive literature reviews, ongoing evaluation of emerging literature is warranted to keep well-informed of developments from research and clinical perspectives given the speed at which mHealth interventions appear (and disappear). Furthermore, existing reviews have evaluated various types of interventions simultaneously, which makes discerning the efficacy of a particular mHealth mechanism difficult. Importantly, no prior reviews have focused on connected interventions for SUD. To address this particular gap, the current review will evaluate the literature on connected health interventions for adults with SUD to reach the following objectives: 1) to describe the current landscape of connected interventions, 2) to determine if connected health interventions for SUD improve clinical outcomes, and 3) to describe usability factors (facilitators and barriers to engagement and acceptability) for connected health interventions in populations with SUD.

2. Methods

2.1 Search Strategy:

This review protocol was registered with PROSPERO, and was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for systematic reviews(PRISMA, 2015). The protocol and search methodology were developed with support from a medical research librarian. A search for relevant articles published from 11/1/13-11/1/18 was conducted using PubMed, IEEE and Scopus databases. The search was conducted using the following search string:

> (“telemedicine”[MeSH Terms] OR “telemedicine”[Tiab] OR “mhealth”[Tiab] OR “mobile health”[Tiab] OR “mobile technology”[tiab] OR wearable[Tiab] OR “smartphone”[MeSH Terms] OR “smartphone”[Tiab] OR “cell phone”[MeSH Terms] OR “cell phone”[Tiab] OR “phone”[Tiab] OR “mobile phone”[Tiab] OR “mobile applications”[MeSH Terms] OR “mobile applications”[Tiab] OR “mobile application”[Tiab] OR “mobile app”[Tiab] OR “connected health”[Tiab] OR “digital health”[Tiab] OR mobile[Tiab])
>
> AND
>
> (“substance-related disorders”[MeSH Terms] OR “substance-related disorders” [Tiab] OR “substance use disorder”[Tiab] OR “analgesics, opioid”[MeSH Terms] OR “opioid analgesics”[Tiab] OR “opioid”[Tiab] OR “cannabis”[MeSH Terms] OR “cannabis”[Tiab] OR “marijuana”[Tiab] OR “cocaine”[MeSH Terms] OR “cocaine”[Tiab] OR “ethanol”[MeSH Terms] OR “ethanol”[Tiab] OR “alcohol-induced disorders”[MeSH Terms] OR “alcohol”[Tiab] OR “behavior, addictive” [MeSH Terms] OR “addictive behavior”[Tiab] OR “addiction”[Tiab] OR “drug abuse”[Tiab])
>
> AND
>
> (effects[Tiab] OR interventions[Tiab] OR outcomes[Tiab] OR usability[Tiab] OR feasibility[Tiab] OR acceptability[Tiab] OR engagement[Tiab] OR barriers[Tiab] OR facilitators[Tiab] OR acceptability[Tiab] OR implementation[Tiab])

Additional key articles were identified via hand search of reference lists of articles identified by the search string and by using the “similar articles” feature in PubMed, the “related documents” feature in Scopus and the “related articles” feature IEEE.

2.2. Eligibility:

Original research, English language articles that included adult participants (age 18 years or older) and focused on SUD, addiction and/or problematic substance use (including alcohol, opioids, marijuana and cocaine) were eligible. Eligible articles needed to both describe a connected health intervention and provide data on one or more outcomes. Connected health intervention was defined as one that meets <u>all</u> of the following three criteria: 1) uses a wearable device and/or mobile phone/app, 2) collects data from a participant (e.g. biologic samples, physiologic data, geolocation, or self-report/Ecological Momentary Assessment), and 3) includes an intervention that was triggered based on data collected from the participant by the device. Eligible outcomes data included any one or more of the following domains: 1) clinical outcomes (e.g. quantitative measures of substance use, abstinence, overdose, craving/desire to use), 2) facilitators or barriers to engagement by either providers or participants, and 3) any measure of feasibility. Articles not describing original research such as review articles, case reports and letters to the editor were excluded.

2.3. Data Abstraction/Study Selection:

A single reviewer screened the initial list of titles and abstracts of identified articles for eligibility. Full texts of all eligible articles and any that were deemed questionable were obtained. All remaining full text articles were reviewed by two reviewers for eligibility criteria, and abstracted data using a standardized tool for those that met inclusion/exclusion criteria (Appendix 1[2]). Data were abstracted in 3 main domains: general population and methodology, mHealth intervention data, and outcomes data. A third author resolved any conflicts related to inclusion/exclusion, data abstraction and/or quality rating.

2.4. Quality Assessment:

The National Heart Lung and Blood Institute's study quality assessment tools for controlled and pre-post intervention studies were used (NHLBI). Articles were given a final rating of good (greater than 70% yes), fair (30-60% yes) or poor (less than 30% OR any 'fatal flaw'). For articles that were strictly qualitative in nature, the Critical Appraisal Skills Programme (CASP) tool for qualitative studies was used(CASP, 2018). The CASP tool does not use a grading scale, but studies were rated by value of the research. Articles were not included or excluded in the review based on quality rating; rather these ratings were used to make an overall assessment of the quality of literature available on the topic.

3. Results

3.1. Overview/Study Selection Process

Details of the study selection are included in Figure 1. We identified 2181 articles in the initial search. After removing duplicates, 1676 unique articles remained. The titles and abstracts were reviewed, and 1553 were excluded based on presence of exclusion criteria resulting in 123 full text articles retrieved. Seventy-five articles were removed based on a full text screen, and the remaining 48 full texts were reviewed in detail with the data abstraction tool. Of these 48, 16 texts were excluded; 15 lacked a connected intervention as defined above and one did not include adult participants. Thirty-two articles were included in the final analysis. Of note, seven articles of the 32 were derived from two large study groups: three described the A-CHESS (Addiction-Comprehensive Health Enhancement Support System) intervention, and four described the Location-Based Monitoring and Intervention for Alcohol Use Disorders (LBMI-A or "Buddy") intervention.

3.2. Study Characteristics

An overview of the 32 included articles is in Table 1. The distribution of articles over the five-year study period is shown in Figure 2, with the highest number of articles published in 2017. The most common study type (N = 13) was a randomized controlled trial. The remaining nineteen articles consisted of nine feasibility articles, seven non-randomized trials, two qualitative articles, and one mixed methods study. The majority of included articles were academic/clinically based, while two were industry based(Attwood et al., 2017; Glass et al., 2017) and four were other or not specified (Dulin and Gonzalez, 2017; Gonzales et al., 2014; Gonzales et al., 2016; Han et al., 2018). The SUDs represented were alcohol (N =20), cannabis (N=3), opioids (N =2), and general or polysubstance use (N =7). None of the articles focused on cocaine use. Twenty-eight articles reported clinical outcomes (i.e. substance use quantity, relapse to use/abstinence, overdose, desire to use/craving, or other). Twenty-three articles reported facilitators or barriers to participant engagement, and user acceptability and feasibility.

Two of the articles used a wearable device, and 31 of the articles used a mobile phone/ application. The parameters measured in the articles included biologic samples, physiologic data, EM A/self-re port, geolocation, and other. Ecological momentary assessment/self-report was the most commonly measured parameter, being utilized in 30 articles. Nine of the reviewed articles employed geolocation as a component of the connected intervention, while four articles utilized connected interventions that responded to biologic or physiologic data collected from the participant. The two articles that incorporated a wearable device used either a biological sample (Barnett et al., 2017) or physiologic data as additional parameters (Leonard et al., 2017).

3.3. Prior Technology Evaluation

Nine out of the 32 articles evaluated participants' prior technology use (Aharonovich et al., 2017; Dulin and Gonzalez, 2017; Dulin et al., 2014; Ford et al., 2015; Giroux et al., 2014; Gonzalez and Dulin, 2015; Guarino et al., 2016; Muench et al., 2017; Zhang et al., 2016). For the majority of these articles, a working knowledge of technology (i.e. basic ability to use texting and email) was listed as an inclusion criterion. The remaining articles did not evaluate prior technology use.

Half of the articles specified participant education on the study app/device as part of their protocol (Aharonovich et al., 2017; Barnett et al., 2017; Beckham et al., 2018; Glass et al., 2017; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Leonard et al., 2017; Muench et al., 2017; Muroff et al., 2017; Shrier et al., 2018; Suffoletto et al., 2016; Witkiewitz et al., 2014; Wright et al., 2018; You et al., 2017). This typically consisted of a tutorial and training of how the technology worked, with a focus on aspects that were needed for the study. For the majority of articles that provided education (N=12) (Aharonovich et al., 2017; Beckham et al., 2018; Glass et al., 2017; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Leonard et al., 2017; Muroff et al., 2017; Shrier et al., 2018; Witkiewitz et al., 2014; You et al., 2017), participants had to demonstrate a working understanding of the technology before completing the enrollment visit.

3.4. Interventions

The most common content noted in the connected interventions was some form of craving management and/or coping assistance (e.g. sending a mindfulness-oriented SMS text when a participant reports a craving) with 26 of the 32 articles including an intervention of this type. All 26 of these articles also employed an intervention to prevent relapse or substance use (e.g. an encouraging SMS text when a participant reports a craving), and six also employed coping assistance after a participant's substance use (e.g. reinforcement of positive behaviors after a reported relapse)(Guarino et al., 2016; Monney et al., 2015; PRISMA, 2015; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016; Suffoletto et al., 2017).

Sixteen of the articles provided some form of feedback, often in response to a participant's progress toward their goals, as part of their connected intervention(Aharonovich et al., 2017; Attwood et al., 2017; Crane et al., 2018; Dulin et al., 2014; Gonzales et al., 2014; Gonzales et al., 2016; Leightley et al., 2018; Monney et al., 2015; Muench et al., 2017; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016; Suffoletto et al., 2017; Wright et al., 2018; You et al., 2017; Zhang et al., 2016). Education about substance use or provision of other types of information was part of the connected intervention in seven of the articles (Aharonovich et al., 2017; Ford et al., 2015; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gustafson et al., 2014; Zhang et al., 2016). Three articles used contingency management as part of the connected intervention, typically in response to successful abstinence (Barnett et al., 2017; Beckham et al., 2018; Dermody et al., 2018). Nineteen of the articles employed multiple forms of connected intervention (e.g. both craving management and tailored performance feedback).

Articles varied in frequency at which the connected intervention was provided. The majority of articles (N= 22) employed connected interventions that only occurred in response to a designated trigger, and were not on a set schedule (Attwood et al., 2017; Barnett et al., 2017; Crane et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Ford et al., 2015; Giroux et al., 2014; Glass et al., 2017; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Leonard et al., 2017; Monney et al., 2015; Muench et al., 2017; Muroff et al., 2017; PRISMA, 2015; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2017; Witkiewitz et al., 2014; You et al., 2017; Zhang et al., 2016). Conversely, 10 articles employed connected interventions that occurred in a regularly scheduled pattern (e.g. participant received daily EMA requests with subsequent intervention based on response): four articles used weekly interventions(Gonzales et al., 2014; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016), three used daily interventions(Aharonovich et al., 2017; Gonzales et al., 2016; Leightley et al., 2018), and two intervened twice daily or more (Beckham et al.,2018; Wright et al., 2018).

The length of interventions ranged from 7-243 days, with a mean of 67 days. The length of total study period and monitoring ranged from 21-913 days, with a mean of 172 days. Five articles used intervention periods shorter than four weeks, 10 articles' intervention periods lasted four to six weeks in duration, and two articles used periods of intervention that were eight weeks in length. Nine of the articles reviewed used an intervention period of 12 weeks and three articles had an intervention period that lasted longer than 12 weeks.

3.5. Outcomes

Reported outcomes are outlined in Table 1. The most common type of outcome used was a quantitative assessment of participants' substance use (e.g. number of drinks per week, number of days with substance use, etc.), seen in 21 articles. Ten articles reported outcome data on participant abstinence, six on substance cravings, and three articles on relapse to substance use. Ten articles included at least one outcome examining quality of life and its relationship to participant substance use and/or the connected intervention (e.g. job loss, financial impact) (Aharonovich et al., 2017; Dermody et al., 2018; Dulin and Gonzalez, 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gustafson et al., 2014; Leightley et al., 2018; Muench et al., 2017; Wright et al., 2018; You et al., 2017). Four articles looked at participants' use of other substances aside from primary substance of interest (Aharonovich et al., 2017; Suffoletto et al., 2015; Witkiewitz et al., 2014; Wright et al., 2018). Four articles attempted to quantify the incidence of participants accessing outpatient recovery services/ resources such as a 12-step program (Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gustafson et al., 2014), and eight articles included substance use-related medical sequelae (e.g. alcohol-related injuries, withdrawal symptoms) as an outcome (Aharonovich et al., 2017; Dermody et al., 2018; Dulin and Gonzalez, 2017; Gonzales et al., 2014; Gustafson et al., 2014; Leightley et al., 2018; Suffoletto et al., 2015; Suffoletto et al., 2017). Four of the articles included at least one outcome related to participants' mental health (e.g. MDD questionnaire)(Aharonovich et al., 2017; Dermody et al., 2018; Leightley et al., 2018; You et al., 2017). One study included money spent on substance use as an outcome(Aharonovich et al., 2017).

For outcomes assessment, a timeline follow-back (TLFB) questionnaire was employed in 11 articles to quantify substance use(Aharonovich et al., 2017; Barnett et al., 2017; Beckham et al., 2018; Dermody et al., 2018; Dulin et al., 2014; Gonzalez and Dulin, 2015; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2014; Suffoletto et al., 2015; You et al., 2017), and 16 of the articles included at least one previously validated survey for the collection of outcome data (Aharonovich et al., 2017; Crane et al., 2018; Dermody et al., 2018; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gonzalez and Dulin, 2015; Gustafson et al., 2014; Han et al., 2018; Leightley et al., 2018; Muench et al., 2017; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2015; Wright et al., 2018; You et al., 2017). Additionally, eight of the articles included an in-person meeting as part of the data collection (Beckham et al., 2018; Giroux et al., 2014; Gonzales et al., 2016; Gonzalez and Dulin, 2015; Guarino et al., 2016; PRISMA, 2015; Shrier et al., 2018; Shrier et al., 2014; You et al., 2017) and seven collected outcome data based on biologic sample testing (e.g. blood alcohol concentration, oral cannabis swab(Aharonovich et al., 2017; Barnett et al., 2017; Beckham et al., 2018; Gonzales et al., 2014; Gonzales et al., 2016; Guarino et al., 2016; Han et al., 2018; Leonard et al., 2017).

Given that many of these articles were testing a novel technology, many (N =11) included feasibility-related outcomes (Aharonovich et al., 2017; Crane et al., 2018; Ford et al., 2015; Giroux et al., 2014; Guarino et al., 2016; Han et al., 2018; Leonard et al., 2017; Muroff et al., 2017; Shrier et al., 2018; Witkiewitz et al., 2014; Wright et al., 2018). Eighteen of the 32 articles chose to include some form of usability or acceptability-related outcome in their assessment(Aharonovich et al., 2017; Barnett et al., 2017; Crane et al., 2018; Dermody et al., 2018; Dulin et al., 2014; Ford et al., 2015; Giroux et al., 2014; Guarino et al., 2016; Han et al., 2018; Leightley et al., 2018; Leonard et al., 2017; Monney et al., 2015; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2017; Witkiewitz et al., 2014; Wright et al., 2018; Zhang et al., 2016), and eight articles investigated an outcome related to participant engagement with either the protocol or the intervention technology itself(Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Leonard et al., 2017; Monney et al., 2015; Muroff et al., 2017; Suffoletto et al., 2016; Suffoletto et al., 2017).

Eleven articles had at least one follow-up assessment or collection of data after the intervention period had ended (Barnett et al., 2017; Beckham et al., 2018; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gustafson et al., 2014; Muench et al., 2017; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2015; Witkiewitz et al., 2014). Twenty-two articles of those reviewed reported outcome data that was analyzed for statistical significance(Aharonovich et al., 2017; Barnett et al., 2017; Crane et al., 2018; Dermody et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Muench et al., 2017; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016; Witkiewitz et al., 2014; Wright et al., 2018; You et al., 2017) with twenty of these articles reporting at least one statistically significant result(Aharonovich et al., 2017; Barnett et al., 2017; Crane et al., 2018; Dermody et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Muench et al., 2017; Shrier et al., 2018; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016; Witkiewitz et al., 2014; You et al., 2017). The remaining 10 articles either reported no quantitative data or did not conduct formal analyses for statistical significance of their results.

3.6. Efficacy of Interventions

With respect to the efficacy of tested interventions, the majority of the included articles demonstrated positive results (N =22); these included interventions targeted at AUD (N =15) (Barnett et al., 2017; Crane et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Glass et al., 2017; Gonzalez and Dulin, 2015; Gustafson et al., 2014; Leightley et al., 2018; Leonard et al., 2017; Muench et al., 2017; Suffoletto et al., 2014; Suffoletto et al., 2015; Suffoletto et al., 2016; You et al., 2017; Zhang et al., 2016), cannabis use (N =3)(Monney et al., 2015; Shrier et al., 2018; Shrier et al., 2014), general SUD (N =4)(Aharonovich et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Muroff et al., 2017) and OUD (N =1) (Guarino et al., 2016). General SUD was defined for the purpose of this study as referencing either greater than one substance use disorder OR SUD not specified. Four articles reported no statistically significant difference in the intervention group with respect to efficacy, including AUD (N=2)(Dermody et al., 2018; Wright et al., 2018) and general SUD (N=2) (Han et al., 2018; Witkiewitz et al., 2014). The remining articles were considered equivocal, either not reporting efficacy data (Beckham et al., 2018; Ford et al., 2015; Giroux et al., 2014) or showing benefit only in a sub population (Attwood et al., 2017; Suffoletto et al., 2017). Multiple studies reported a notable difference in engaged users, with better results (increased efficacy) in participants who appeared more engaged based on predefined use metrics (Attwood et al., 2017; Leightley et al., 2018; Suffoletto et al., 2017; You et al., 2017). Few articles included data on long term follow up: of those that did, four showed sustained behavior change at 3-9 month follow up (Gonzales et al., 2014; Gonzalez and Dulin, 2015; Gustafson et al., 2014; Shrier et al., 2014), and one failed to show sustained change at one month(Barnett et al., 2017).

3.7. Usability Factors (Barriers, Facilitators, and Acceptability)

Overall, 23 out of 32 articles included data pertaining to usability factors. Nineteen reported specific barriers, facilitators, or other recommended solutions, which are highlighted in Table 2. These include factors such as user difficulty using unfamiliar technology, inability to afford smart phone payment plans, and hardware theft or damage. For example, Guarino et al found that only 44% of participants undergoing methadone maintenance therapy returned the original smart phone provided to them during a study investigating a mobile intervention, and many reported technical difficulties using the phones provided during the study.

Participant literacy was addressed as a factor that may have influenced the outcome of one of the 32 articles; Muroff et al speculated that low functional literacy may have affected the use of some of their mobile intervention's features, and they were concerned that a significant proportion of their Latino population may have lacked basic literacy skills. They proposed increased access to audio materials as one potential remedy for this barrier(Muroff et al., 2017). Only two articles specified a minimum reading competency grade-level as part of their inclusion/exclusion criteria(Dulin et al., 2014; Muench et al., 2017).

Overall, acceptability was high. Of the 22 articles that reported data on acceptability and feasibility, 20 included results from either a survey or interview after the intervention (Aharonovich et al., 2017; Attwood et al., 2017; Barnett et al., 2017; Beckham et al., 2018; Crane et al., 2018; Dulin et al., 2014; Giroux et al., 2014; Guarino et al., 2016; Han et al., 2018; Leightley et al., 2018; Leonard et al., 2017; Monney et al., 2015; Muench et al., 2017; Shrier et al., 2018; Shrier et al., 2014; Suffoletto et al., 2017; Witkiewitz et al., 2014; Wright et al., 2018; You et al., 2017; Zhang et al., 2016). Other measurements included the proportion of users still actively engaging with an intervention at a predefined point in time(Attwood et al., 2017; Muroff et al., 2017), the daily frequency of interaction with the mHealth intervention (Aharonovich et al., 2017; Monney et al., 2015), time spent using a mobile application (Aharonovich et al., 2017; Leightley et al., 2018; You et al., 2017), and the proportion of participants who elected to continue the intervention after the study period ended (Muench et al., 2017; Suffoletto et al., 2017).

Only two articles reported usability data for a sensor device that was not a smartphone or personal digital assistant (PDA) (Barnett et al., 2017; Leonard et al., 2017). Barnett et al reported that out of 29 participants who wore a transdermal alcohol sensor bracelet, 79% indicated willingness to wear the sensor for an additional week after the study ended. In contrast, Leonard et al reported that of 10 participants who wore a sensor bracelet, approximately half felt the band was "uncomfortable," "bulky," or "too large" (Leonard et al., 2017).

Fifteen of the articles provided a dedicated study phones to participants in lieu of using their own phone (Aharonovich et al., 2017; Beckham et al., 2018; Dermody et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Giroux et al., 2014; Glass et al., 2017; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Leonard et al., 2017; Muroff et al., 2017; Shrier et al., 2018; Witkiewitz et al., 2014; You et al., 2017). This strategy was considered less acceptable and feasible by study participants. For example, Dulin et al found that 61% of participants indicated that they would have engaged with the system more often if it had been on their own phone or a better phone that that provided by the study (Dulin et al., 2014). Leonard et al reported that users frequently forgot to charge devices that were not their regular phones and were reluctant to carry more than one device during their daily routines(Leonard et al., 2017).

Nine interventions included a Global Positioning System (GPS) component, which generally had poor acceptability among study participants. Attwood et al reported that among the only 14% of study participants who chose to define a physical location as a drinking “weak spot,” most users turned off the GPS based feature that sent a supportive notification when they were in physical proximity to that location. Qualitative interviews with study participants indicated that interviewees more commonly felt triggered to consume alcohol by social gatherings, emotion, or time than by physical location (Attwood et al., 2017). Dulin et al reported that users found the high-risk location tool intriguing, but ultimately unhelpful due low reliability in triggering near the user-defined locations(Dulin et al., 2014).

Cultural preferences were also noted to be important; Han et al found low overall response rates for EMA data collection among those with SUDs in China. The authors hypothesize that common stigma of immorality associated with SUD in Chinese culture and resultant isolation limited the participants’ comfort with mobile EMA; consequentially, participants preferred face-to-face interviews (which were perceived as a way to communicate with the public). Post-intervention surveys revealed that some participants worried about the privacy within the app and were afraid that submitting information regarding relapse could have legal ramifications (Han et al., 2018). In contrast, a study targeted toward ex-military personal with AUD in the UK demonstrated high acceptance and engagement with a mobile app for AUD in this population (Leightley et al., 2018).

One study explored the feasibility of long-term implementation of their mHealth. Ford et al described six key strategies used to sustain long-term use of their A-CHESS mobile app intervention. These strategies included strong support from agency leadership, clearly-defined strategies to engage staff, deliberate monitoring of client engagement with the intervention and efforts to follow-up with clients with low engagement, developing a business model strategy that included ongoing use of mHealth interventions, creation of internal work groups to monitor ongoing intervention use, and creation of guidelines to help clients use the interventions(Ford et al., 2015).

3.8. Perceived Bias and Quality ratings of included articles

There was at least some degree of perceived bias or conflict in approximately one third of the articles, which was predominantly related to the authors being the creators or owners of the product being tested. Six articles were deemed predominantly qualitative in nature and were evaluated using CASP (Ford et al., 2015; Giroux et al., 2014; Leonard et al., 2017; Monney et al., 2015; Suffoletto et al., 2017; Zhang et al., 2016). Thirty three percent of articles were rated as minimally valuable, where the remaining 67% were judged to be of value. The distinction between these two groups of studies generally was in the methodology and analytic plans; those of deemed low value had poorly defined qualitative methodology and lacked rigorous qualitative data analysis while the valuable studies had more rigorous methodology and analytic plans. All articles had a clear stated aim for the research and a clear statement of findings. Interestingly, few of the articles addressed the CASP question items regarding the relationship between the researcher and the participants and ethical issues.

The remaining 26 articles were evaluated using NHLBI scales: Nine articles were evaluated using the “no control group” tool (Attwood et al., 2017; Beckham et al., 2018; Dulin and Gonzalez, 2017; Dulin et al., 2014; Leightley et al., 2018; Muroff et al., 2017; Shrier et al., 2014; Suffoletto et al., 2016; You et al., 2017), and 17 articles were evaluated using the “controlled intervention studies” tool(Aharonovich et al., 2017; Barnett et al., 2017; Crane et al., 2018; Dermody et al., 2018; Glass et al., 2017; Gonzales et al., 2014; Gonzales et al., 2016; Gonzalez and Dulin, 2015; Guarino et al., 2016; Gustafson et al., 2014; Han et al., 2018; Muench et al., 2017; Shrier et al., 2018; Suffoletto et al., 2014; Suffoletto et al., 2015; Witkiewitz et al., 2014; Wright et al., 2018). Fifteen percent were rated as poor; predominant reasons for low quality ratings included very small sample size, and lack of meaningful statistical analysis. Fifteen percent were rated as good, all were RTCs. The majority (70%) were rated as fair; among these many were pilot and/or feasibility studies that were well designed but underpowered. Notable rating categories where non-controlled studies lost points for on the quality scale were sample size, blinding and representativeness of samples. Many were small, non-blinded studies using convivence type samples. Notable rating categories where controlled studies lost points for on the quality scale were sample size and blinding. Many were again small sample sizes and over 50% lacked any mechanism for blinding in the protocol. Of note, few articles lost points on the tools due to poor attrition or adherence, and most used an intention to treat (ITT) analysis, which bolstered their quality score.

4. Discussion

In our review of studies on connected mHealth interventions, several common themes arose including: focus on AUD or general SUD, use of EMA as a data collection strategy, and use of craving management or coping assistance as an intervention. Studies using objective data sources such as physiologic or biologic sampling to trigger their intervention were uncommon.

In general, connected interventions were associated with decreased craving and substance use while the interventions were in use, and several articles noted sustained behavior change at short term (3-9 month) follow up. Several articles did report adherence decreasing over time, which is a known limitation of engagement with health apps(Krebs and Duncan, 2015). Since the included articles were heavily weighted toward an AUD focus, it is difficult to assess whether efficacy varied by SUD. It is worth noting that all articles targeting cannabis use disorder demonstrated positive results.

Successful adoption of mHealth treatment modalities is predicated by a unique set of challenges. The majority of the studies included an assessment of usability, which is crucial for interventions where user engagement is key to success (like most mHealth interventions). This is supported by the fact that multiple articles indicated a stratified response, with highly engaged users having better outcomes than less engaged users. Acceptability was generally high, however mHealth interventions are not likely to be "one size fits all." Further evaluation into which features of these platforms work best for various demographic groups will be crucial to success. Age for example, may play a key role. In the present group of articles, samples tended to be skewed toward younger populations, with many particularly focused on college aged participants and none focused on older adults. Cultural factors may also play a large role and will require tailoring of interventions. Given that our search was limited to English language articles we were not able to explore this fully, but several articles did touch on the issue. For example, Muroff, et al noted that in a Latino population, acceptance for a mobile app for AUD was high. However, Han et al noted that in a population of Chinese participants with SUD, acceptability and uptake were low, and the authors cited cultural barriers as a major factor.

The quality of the mHealth articles reviewed was higher than expected for this relatively young field, with many RCTs included. Some of the limitations encountered that hampered quality were inherent in digital health studies; for example, small sample sizes may be reflective of the need to complete investigations on a shorter timeline in order to avoid a lapse in the technology being tested. Strategies to overcome these limitations and increase the robustness of mHealth research in general should be sought. These may include using more device and/or platform agnostic approaches to improve translation to newer devices and reduce the risk of technology lapse. Also, creating large, multicenter data repositories, and/or leveraging existing industry datasets from consumer devices could overcome the issues related to small sample sizes and limited data.

Our results have several implications for clinical treatment paradigms. As suggested by many of the authors in this group of articles, connected interventions may serve as a more cost efficient and flexible alternative to in-person behavioral health services for individuals whose access to these services is impaired due to financial or logistic reasons. However, it is more likely that they will serve as an adjunct and/or an extension of traditional clinician delivered behavioral interventions and medications. Also, any attempts to integrate mHealth platforms into clinical care should strongly consider logistics and user preferences, as these may present insurmountable barriers to implementation. Features like the ability to use one's own phone for the intervention (as opposed to a separate device) repeatedly emerged as a must-have feature if use is to be sustained.

With respect to future research opportunities, a largely unexplored area in this space is the incorporation of wearable sensors (or other passive, objective data collection tools) to trigger connected interventions. While many of the EMA focused articles demonstrated engagement, the requirement for effort and active participation of the part of the user will inevitably lead to missed opportunities and missing data. Supplementing, or even replacing, EMA with digital biomarkers that signal high risk states represents a powerful and underexplored area of opportunity for connected interventions that could minimize effort on the part of the user and maximize efficacy. Beyond digital biomarkers from a single wearable, the related concepts of context sensing and predictive analytics may provide even more powerful ways to passively collect data and predict problematic behaviors. Although in their early stages, these concepts are already being applied to electronic medical record, social media and even personal device data to understand and predict risk substance use (Bae et al., 2018; Hassanpour et al., 2019; Lauvsnes et al., 2020). Driving mHealth interventions with passive data collection will undoubtedly increase utility, convivence, compliance and acceptability.

5. trengths and Limitations

Our systematic review has several strengths that enhance its value to the academic community, including the use of a multidisciplinary set of databases and evaluation of both quantitative and qualitative outcomes to increase the breadth of articles included in the review. There are also limitations to our review. Some terminology related to mHealth is ambiguous, with different authors referring to the same technology by different names. We did attempt to capture this in our search string, however there is a possibility that some pertinent articles were not captured. Positive publication bias may have led to an inflated sense of effectiveness of the mHealth technology. Inclusion of only English language articles in the search may have missed important articles published internationally in alternative languages and may have caused us to overlook important cultural differences in the data. Finally, some mHealth research driven by industry may not be represented in the peer reviewed literature, and thus would not have been captured in this review.

6. Conclusions

The majority of articles in this review of connected interventions reported positive effects on SUD recovery metrics and overall high acceptability. Several themes were identified among the current body of literature included a focus on AUD, use of smart phones, and use of EMA as a data collection tool. Wearables that directly monitor biologic data and predictive analytics using integrated data streams represent understudied opportunities for new original research in this space.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- Connected interventions use data from mHealth devices to trigger interventions
- Connected interventions have the potential to dramatically impact SUD treatment
- Many connected interventions focus on AUD, use smart phone and use EMA
- Most studies reported positive effects on SUD outcomes and high acceptability
- Few connected interventions to date utilize wearables to monitor biologic data

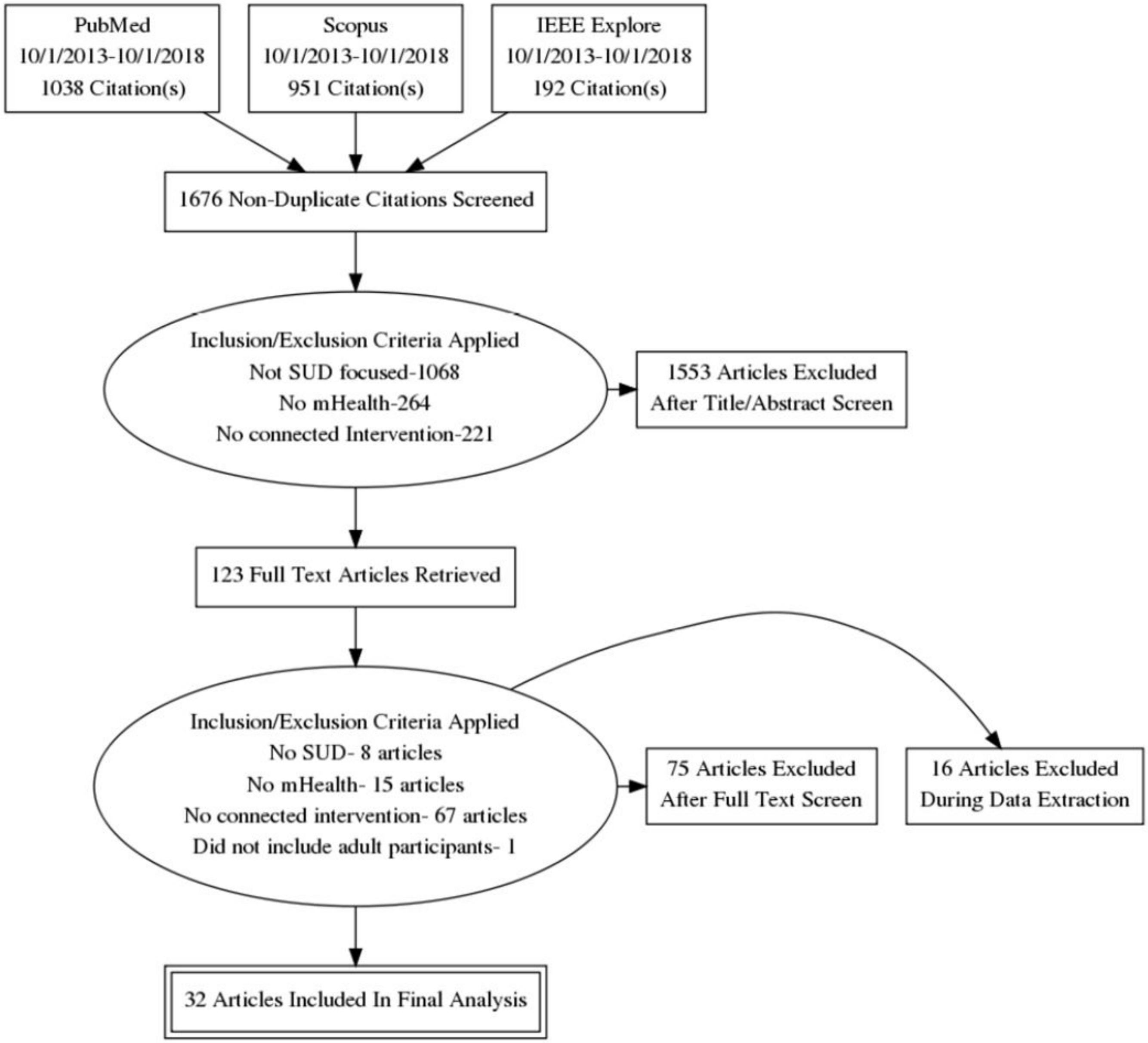

Figure 1:
Article Selection Process

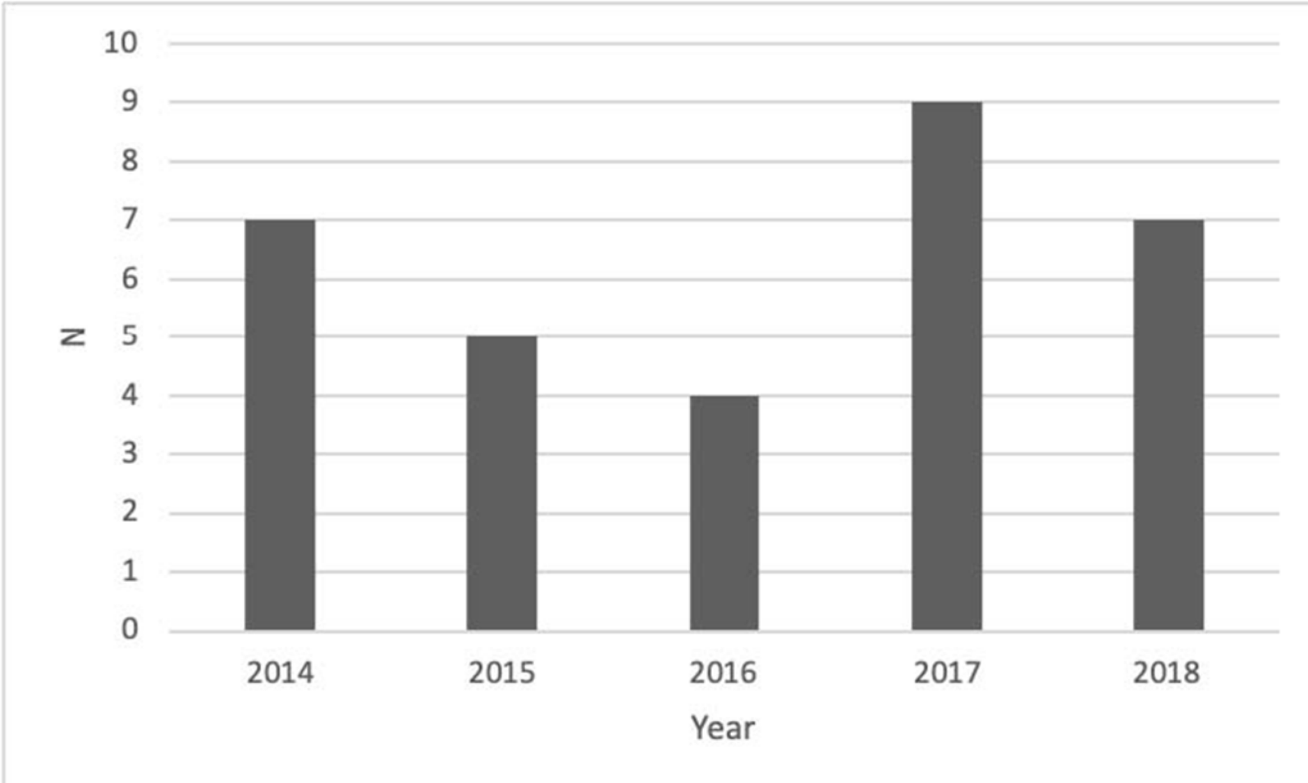

Figure 2:
Number of Articles by Year

Table 1:

Characteristics of Included Articles (N = 32)

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains			
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability	Outcomes	Key Findings
A-CHESS (Addiction-Comprehensive Health Enhancement Support System) *OC, OP*	AUD	Qual	44	50%	20-54		X	Ford 2015	EMA, Geo	• Targeted feedback based self-reported craving data and high-risk physical location data that indicated EtOH relapse risk	N/A		X	• Perceptions of sustainability, barriers, and impact of A-CHESS	• Top innovative features of the app identified were the discussion group and the ability to address client needs and provide rapid staff support
	AUD	RCT	349	39%	NR (mean = 38.3)		X	Glass 2017	EMA, Geo	• See Ford 2015	8 months	X		• # of risky drinking days • Abstinence/ probability of abstinence	• Reduced risky drinking days • Increased abstinence • Increased use of outpatient addiction treatment
	AUD	RCT	349	39%	NR (mean = 38)		X	Gustafson 2014	EMA, Geo	• See Ford 2015	8 months	X		• # of risky drinking days	• Fewer risky drinking days and a higher likelihood of consistent abstinence during the intervention and at 4 month follow up
AGATE-Rx & SASED *SD*	AUD	RCT	76	29%	21-55 (mean = 38)		X	Dermody 2018	EMA	• Text reminders with hyperlinks to website for naltrexone adherence reporting • Text frequency was adaptive based on reporting	8	X	X	• Naltrexone adherence • Desire to drink/ craving • Quantity of EtOH use	• Adherence declined over time, with no difference in adherence between control and intervention • No difference in EtOH craving
CASA-CHESS *OC, OP*	Gen	NRT	79	11%	24-65		X	Muroff 2017	EMA, Geo	• See Ford 2015	4 months	X	X	• # of days app used, % still using app at 4 months	• Engagement among Latinos participants was high • Usage was maintained over the study period with messages, discussion boards, and surveys being the most highly used features
Check-In Program *C*	OUD	MM	50	18%	21-63		X	Guarino 2016	EMA	• Personalized feedback and development self-management strategies for opioid use	12 weeks	X	X	• Treatment retention • # opioid abstinent days • Acceptability	• Increased retention in treatment and abstinence from opioids • Feasible approach and highly acceptable

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains			
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability	Outcomes	Key Findings
										triggers based on EMA					
Drinkaware[SD]	AUD	MM	119 k	59%	17-75+		X	Attwood 2017	EMA, Geo	• Supportive notifications when passing a geographic “weak spot” • Monitoring and feedback on patterns of EtOH consumption related to personal goals	12 weeks	X	X	• Units of EtOH consumed per week • # of binge sessions per week • # of “no drink days” per week • Perceived usability and effectiveness	• EtOH consumption was reduced only in highly engaged users and appeared to plateau after one week • Acceptance was high and app appeared to increase awareness and self-monitoring of EtOH consumption • High attrition overall
Drink Less[SD]	AUD	RCT	672	56%	NR (mean = 39.2)		X	Crane 2018	EMA	• Goal setting • Normative feedback based on drinking compared to other app users • Self-monitoring and feedback on EtOH use and consequences • Cognitive bias re-training	28 days	X	X	• Change in EtOH consumption, change in AUDIT score • App usage	• No significant main effects on change in weekly EtOH consumption or AUDIT score; some two-way interactions between particular modules and outcomes • Mean app usage was 11.7 sessions and 8/28 days
Health-call[C]	Gen	RCT	47	23%	34-63		X	Aharonovich 2017	EMA	• Tailored video clips of a virtual counselor based on app use and EMA data (i.e. achieving sobriety goals)	60 days	X	X	• # of days of primary drug use • Time spent per day using the app • Overall satisfaction with app • Amount spent per day on drugs • # of standard drinks per day	• Incidence rate ratio in app users was 0.59 (p=0.04) over 60 days compared to control • Median daily use of app was 95% • High satisfaction with app
Index[SD]	AUD	F	31	13%	25-64		X	Leightley 2018	EMA, Geo	• Personalized text messages based on EMA reported EtOH consumption and mood symptoms	4 weeks	X	X	• # of drinking days and drink-free days • Standard EtOH units per drinking day • Total # of standard EtOH units consumed over the course of the study, and # of alcoholic drinks consumed per drinking day	• Reduced drinking days and # of drinks per drinking day • Users primarily used the app to monitor # of drinks consumed • Feasible and acceptable among ex-military serving individuals

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains		Outcomes	Key Findings
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability		
Location-Based Monitoring and Intervention for Alcohol Use Disorders (LBMI-A or "Buddy") *SD*	AUD	F	28	46%	22-45		X	Dulin 2014	EMA, Geo	• Multiple tools including: • Craving management • Drink monitoring • Problem management • Supportive Persons • High Risk Locations	6 weeks	X	X	• Alcoholic drinks per day and % days with hazardous drinking	• Significant reductions in % of heavy drinking days, mean # of drinks per day, and drinks per drinking day • Overall usability was reported as high • Increased awareness surrounding EtOH consumption
	AUD	NRT	34	48%	22-45		X	Dulin 2017 *SD*	EMA, Geo	• See Dulin 2014	6	X		• Craving type and strength • EtOH use in response to craving	• Reduction in craving cued drinking • "Supportive person" tool less effective than the other features
	AUD	Qual	28	47%	22-45		X	Giroux 2014	EMA, Geo	• See Dulin 2014	6 weeks		X	• Perception of barriers to use, helpfulness, and utility app	• Five main themes identified by users as most helpful • Awareness • Accountability • Skill Transference • Tracking Progress • Accountability Prompts
	AUD	NRT	60	42%	NR (mean = 34)		X	Gonzalez 2015	EMA, Geo	• See Dulin 2014	6 weeks	X	X	• % days abstinent • % heavy drinking day • Mean # drinks per week	• Increase in % days abstinent • Decrease in % heavy drinking days and mean drinks per week
Mema, llumivu, Inc. *C*	MJ	RCT	70	42%	NR (mean = 21)		X	Shrier 2018	EMA	• Personalized messages based on marijuana use or desire to use	2 weeks	X	X	• % days abstinent • Motivation to reduce marijuana use • Perceived acceptability and usefulness	• Decreased marijuana use and desire to use
Mind the Moment App, Emaptica E4 (sensor) *C*	AUD	F	11	100%	19-22	X	X	Leonard 2017	EMA, Physiologic	• Personalized messages and educational content based on electrodermal activity measured by the wearable sensor	3 weeks		X	• User perception of effectiveness in helping decrease risky drinking • Validity of alerts and general satisfaction	• High level of acceptability • Perceived as easy to use, effective in helping reduce risky drinking, and valid alerts
Secure Continuous Remote EtOH Monitor	AUD	RCT	30	47%	21-57	X		Barnett 2017	Biologic	• Monetary reinforcement for days when no drinking was	3 weeks	X	X	• % of days with no drinking detected by sensor • Longest # of	• Contingency management group had a higher % of days with no EtOH

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains			
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability	Outcomes	Key Findings
(SCRAM II and SCRAMx) [SD]										reported or detected by a transdermal EtOH sensor				consecutive days with no drinking • Peak transdermal EtOH • # of drinks per week • Perceptions regarding side effects of the sensor	consumption (p =0.053), and longer periods of consecutive no drinking days
Sober-diary [SD]	AUD	NRT	38	29%	NR (mean = 42.2)		X	You 2016	EMA, Biologic	• Personalized feedback and rewards based sobriety (via mobile breathalyzer)	12 weeks	X		• Adherence • # of drinking days and heavy drinking days • # of drinks per week and per drinking day • % and # abstinence days • Time to relapse	• High adherence to the intervention associated with lower drinking frequency/ amount, higher # of abstinence days, less anxiety, and increased quality of life.
Stop-cannabis [SD]	MJ	F	482	30%	15-60+		X	Monney 2015	EMA	• Personalized messages based relapse to cannabis use or based on user entered goals for quitting	N/A	X	X	• Perceived helpfulness in reducing cannabis use and overall usefulness • Frequency of use	• Acceptability and perceived helpfulness were high
NR [C]	Gen	F	5	80%	35-57		X	Beckham 2018	Biologic	• Monetary reinforcement for abstinence and for compliance (uploading videos of CO breathalyzer + THC oral fluid sample) + CBT	4 weeks	X	X	• Interrater reliability for video facilitated oral fluid testingy • Video upload rate by participanty • Daily abstinence from cannabis and tobacco	• Interrater reliability was 100% • Rates of video test upload by participants were 61.3% and 70% for cannabis and tobacco, respectively
NR [SD]	Gen	F	80	27%	14-26		X	Gonzales 2014	EMA	• Tailored text message feedback based on mood, substance use, and recovery	12 weeks	X		• Differences in primary drug use relapse by study condition over time	• Reduced rate of relapse to primary drug • Increased engagement in extracurricular recovery behaviors
NR [SD]	Gen	F	80	29%	14-26		X	Gonzales 2016	EMA	• See Gonzales 2014	12 weeks	X		• Relapse to substanceuse	• Decreased likelihood to test + for primary drug at 6 and 9 month follow up • Increased engagement in extracurricular recovery behaviors 6

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains		Outcomes	Key Findings
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability		
															and 9 months post intervention
NR *SD*	Gen	RCT	75	29%	NR (mean = 42)		X	Han 2018	EMA	• Personalized messages based on EMA reported cravings and drug use	4 weeks	X	X	• Days of drug use • # of drugs used • Craving (self-report)	• Poor agreement between EMA and urine testing • Low acceptance of mHealth among individuals with SUDs in China
NR *SD*	AUD	RCT	176	74%	NR (mean = 43.2)		X	Muench 2017	EMA	• Personalized text messages about personal EtOH consumption and goals based on EMA report	12 weeks	X		• # of drinks per week, # of heavy drinking days per week, and # of days per week without drinking • Desire to continue the intervention • Short Inventory of Problems questionnaire	• Reduction in weekly drinking • The greatest effects were on reduction in the # of heavy drinking days, rather than increasing the # of days without any drinking • 80% of participants expressed a desire to continue receiving texts after the study period
NR *C*	MJ	NRT	27	70%	15-24		X	Shrier 2014	EMA	• Personalized messages based on EMA reported marijuana use or desire to use	4 weeks	X	X	• Motivation to reduce marijuana use • Perception of ease of use • % days abstinent	• Decreased desire to use marijuana in relation to triggers and decreased use after triggers from baseline to three months post-intervention • Ease of use, feasibility and acceptability were supported
NR *SD*	AUD	RCT	858	65%	18-25		X	Suffoletto 2014	EMA	• Personalized feedback basedon EMA reported EtOH use	3 months	X	X	• EtOH use frequency and quantity (on a drinking day) • Binge drinking • % response to prompts	• Reductions in binge drinking days and the # of drinks consumed per drinking episode up to 3 months after discharge • Initial response rates were high, but dropped significantly by week 12
NR *SD*	AUD	RCT	765	65%	NR (mean = 22)		X	Suffoletto 2015	EMA	• Personalized goal setting requests based on intent todrink • Personalized feedback based on EtOH use	12 weeks	X		• # of binge-drinking days and binge drinking prevalence • Drinks per drinking day • EtOH-related injury prevalence	• Reduction in binge drinking days and lower binge drinking prevalence • Less drinks per drinking day and lower prevalence of EtOH related injuries

App/Device Name	SUD	Study design	Sample Characteristics			Modality		Record ID	Parameters	Description of Connected Intervention	Duration	Outcome Domains			
			N	% female	Age range (years)	Sensor	Mobile phone/ app					Clinical	Usability	Outcomes	Key Findings
NR *SD*	AUD	NRT	224	46%	NR (college under graduates)		X	Suffoletto 2016	EMA	• Personalized goal setting requests based on EMA reported intent to drink • Personalized feedback based on EMA reported EtOH use	6 weeks	X		• Response rate • Willingness to commit to drinking limit • # of drinks on a single occasion • # of weekend binge drinking episodes • Intent to drink over the weekend	• Engagement was high • Drinking-limit goal commitment was associated with less EtOH consumption • Feasibility was supported
NR *SD*	OUD		20	55%	21-56		X	Suffoletto 2017	EMA	• Personalized feedback on relapse avoidance based on craving or drug use	7-28 days	X	X	• Daily urge to use opioids • Opioid abstinent days	• Response rates were poor, participants who did respond reported benefit • Participants felt empowered, but some reported queries about cravings triggered cravings
NR *SD*	Gen	RCT	94	28%	NR (mean = 20.5)		X	Witkiewitz 2014	EMA	• Motivational interviewing ("urge surfing") module delivered at time of craving	14 days	X	X	• Daily drinking questionnaire (DDQ) • Young Adult Alcohol Problems Screening Test (YAAPST) • Daily Smoking Questionnaire (DSQ)	• No reductions in drinks per drinking day, days of heavy drinking, or EtOH related problems • Prompts increased cravings to smoke in subset • Feasibility was supported
NR *SD*	AUD	RCT	269	48%	18-29		X	Wright 2018	EMA	• Personalized feedback on EtOH consumption measured by self-report	12 weeks	X	X	• Peak # of drinks consumed in a single night • Feasibility and acceptability of app	• No difference in EtOH consumption measures or EtOH-related harms • Participants rated messages as useful
NR *SD*	AUD	F	116	34%	10-69		X	Zhang_2015	EMA	• Personalized feedback on EtOH consumption measured by self-report	NR		X	• User perception on usefulness of various app features	• Participants were accepting of app and perceived it as moderately useful

EtOH= Alcohol

NR= Not reported

Study Design: Geo= Geolocation MM = Mixed methods, NRT- Non-Randomized Trial, RCT-Randomized Controlled Trial, Qual = Qualitative, F = Feasibility

SUD: AUD- Alcohol Use Disorder, Gen- General Substance Use Disorder, MJ- Cannabis Use Disorder

SD: The intervention was entirely self-directed;

C: Participants met with a counselor at least once during the intervention as an adjunct to therapy;

OC: Participants in the intervention group had the option of engaging with a counselor at least once as an adjunct to therapy;

OP: Participants in the intervention group had the option of engaging with peers at least once as an adjunct to therapy.

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Table 2:

Articles Including Usability Factors: Facilitators, Barriers, and Recommended Solutions = (N =19):

App/Device Name	Record ID		Facilitators to Engagement	Barriers to Engagement	Other Recommended Solutions
A-CHESS (Addiction-Comprehensive Health Enhancement Support System)	Ford 2015		• Strong administrative support for adaptation • Recognition by administration of innovation and necessity • Dedicated resources for training and sustaining participation • Feature to create a pleasurable activity plan as an alternative to drinking	• Lack of external financial support (from payers) • Lack of communication about app to staff, and from staff to clients • Long load times • Connectivity issues • Low technology literacy among older clients • Concerns about "being tracked" with GPS feature in subset of clients	• Concrete and ongoing staff training about the technology integration • Routine review of use and updating of protocols to re-engage as needed • Dedicated staff (e.g. task force, internal champions) • Proactively developing a business model to support use
AGATE-Rx & SASED	Dermody 2018		• Adherence promotion by booster interventions following heavy drinking and strong craving days		
CASA-CHESS	Muroff 2017		• More dynamic app features (e.g. message boards/forums) that require ongoing participation were more engaging overall than static features (those that didn't change over time)	• Concern that literacy was a problem both for people with AUD and for those in the Latino community	
Check-In Program	Guarino 2016		• Novel information in app helped clarify misconceptions about opioid use	• Need for additional technical assistance beyond the initial tutorial • Limited content perceived as "boring" • Content difficult to use on small screen of the study phones • Lack of experience with smartphone technology in lower-income, middle-aged, and minority participants	• Addition of modules to address other drugs of abuse • Connection to additional resources (24-hour helpline and local 12-step/recovery support) • Text messages with personalized content • Voice-over narration of text to improve usability for users with vision/reading difficulties • Application that could be installed on participants' own mobile phone • Addition of a social support or human interaction component
Drinkaware	Attwood 2017		• Numeric feedback for users to quantify their drinking in terms of calories/dollars	• Poor user understanding and perception of GPS defined "weak spot"	• Social or emotional triggers may be better than geographic ally defined "weak spots"
Drink Less	Crane 2018		• Increased usage in response to self-monitoring/feedback		
Health-call	Aharonovich 2017		• Video counselors reinforcing qualities (e.g. being comforting, soothing, and encouraging)		

App/Device Name	Record ID		Facilitators to Engagement	Barriers to Engagement	Other Recommended Solutions
			• Simple app design with audio and visual instructions		
Index	Leightley 2018		• Personalized goal setting and feedback tailored to individual's goals	• If-then type goal setting function was infrequently used and poorly rated	
Location-Based Monitoring and Intervention for Alcohol Use Disorders (LBMI-A or "Buddy")	Dulin 2014		• Easy to use tools • Awareness building with daily interview tool • Information on craving and finding nondrinking pastimes	• Need for a separate study cell phone • High-risk location tool malfunction (going off at the wrong location)	• Personalization • Availability of the system on a user's personal phone • Alerts disguised as ordinary phone sounds to reduce stigma • Self-contained device/app itself (avoid using external websites) • Prioritizing ease of use of the user interface • Using frequent prompts to maintain user engagement
	Giroux 2014		• Enhanced engagement with prompts for entering number of daily drinks or reminders for specific features • Skills were transferable to daily life • Personalized goal setting, progress tracking, and accountability	• App only available on study smartphone (not participant's personal phone)	• More rich and engaging prompts for user engagement (graphics, etc.) • Capitalize on the motivational aspects of seeing your progress over time
	Gonzalez 2015			• Passivity of system limited long term use	• More system prompts to maintain user engagement • Provide the intervention as a downloadable app on personal smartphone • Tailor intervention across a full range of disease severities
Mema, llumivu, Inc.	Shrier 2018		• Low cost	• Perception that users can "cut back or quit on their own" • Too many reports	
Mind the Moment App, Emaptica E4 (sensor)	Leonard 2017		• Increased awareness prompted by the sensor	• Device was uncomfortable/bulky/large • Difficult remembering to charge both the phone and the sensor • Bluetooth malfunction • Band was conspicuous and required explanation • Carrying study phone and personal phone was burdensome • Participants forgetting to use the technology • Alerts at inopportune times	• Install the app on participants' personal phones • Using GPS coordinates or users' class schedule to avoid setting off alerts at inopportune moments • Utilize commercial/mainstream wearable devices to minimize burden
NR	Han 2018			• Concerns with privacy and fear of legal consequences • Discomfort with GPS function of the app	

App/Device Name	Record ID		Facilitators to Engagement	Barriers to Engagement	Other Recommended Solutions
	Shrier 2014			• Use of a PDA instead of smartphones perceived poorly	• Providing compensation after each period of momentary and daily reporting, and maintaining contact with participants between study visits • Use smartphones and text message reminders
	Suffoletto_2017			• Low perceived importance of SUD treatment lead to low engagement • Some users were in treatment programs that did not allow the use of cell phones and thus limited their participation in the intervention	
	Wright_2018		• Brief intervention messages kept participants more engaged in the intervention	• Long delays between technology conception/pilots and actual intervention • Ethics committees' requirements made the description of the study procedures complex and daunting for participants • Technical problems with their intervention (questionnaire links not being sent on a requested night, questionnaire links being sent after participants had opted out, and some feedback messages not being sent for the intervention)	• Combining visual and verbal description of the study procedures might be more suitable for complex interventions.
	Zhang_2015			• Application limited to Android users	• Expanding technology availability to multiple platforms
Secure Continuous Remote EtOH Monitor (SCRAM II and SCRAMx)	Barnett 2017			• Physical discomfort (itching and sweating) and social discomfort cause by wrist sensor • Interference with daily activities by sensor	