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mHealth for the Detection and Intervention in Adolescent and Young Adult Substance Use Disorder

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Abstract

Purpose of review—The goal of this review is to highlight recent research in mHealth based approaches to the detection and treatment of substance use disorders in adolescents and young adults.

Recent findings—The main methods for mHealth based detection include mobile phone based self-report tools, GPS tracking, and wearable sensors. Wearables can be used to detect physiologic changes (e.g., heart rate, electrodermal activity) or biochemical contents of analytes (i.e. alcohol in sweat) with reasonable accuracy, but larger studies are needed. Detection methods have been combined with interventions based on mindfulness, education, incentives/goals and motivation. Few studies have focused specifically on the young adult population, although those that did indicate high rates of utilization and acceptance.

Summary—Research that explores the pairing of advanced detection methods such as wearables with real time intervention strategies is crucial to realizing the full potential of mHealth in this population.

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Compliance with Ethics Guidelines

Conflict of Interest

Stephanie Carreiro has received a grant from RAE Healthcare to investigate the use of wearable sensors for stress and craving during treatment for substance abuse disorder.
Peter R. Chai declares that she has no conflict of interest.
Jennifer Carey declares that she has no conflict of interest.
Jeffrey Lai declares that he has no conflict of interest.
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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).

Keywords

Substance Use Disorder; Technology; mHealth; Treatment; Young adults; Wearables

I. Introduction

The staggering prevalence of substance use disorder (SUD) in the young adult population[1] has created an urgent need for effective, innovative strategies for its detection and treatment. Traditional SUD treatment options are often designed for adults. Developmental and lifestyle factors specific to adolescents and young adults with substance use should be considered as additional factors when designing treatment protocols for this population[2,3]. Mobile health (mHealth) based platforms leverage the existing technology embedded in young people's lifestyle to assess and treat SUD in ways that traditional treatment approaches often fail to achieve.

Technology based approaches broadly refer to diagnostic and treatment strategies that utilize computers, the internet and mobile devices as delivery vehicles. The term "mHealth" specifically refers to the utilization of mobile devices, while e-Health is used to describe web- or computer based strategies. Mobile devices include mobile phones (especially smartphones with internet and application or "app" capabilities) and wearable devices (smartwatches, adherent patches, and other sensors that are applied to the body for the purpose of *in vivo* monitoring). Wearables and mobile phones together provide a powerful combination that allows for both detection and real-time intervention deployment: Adolescents and young adults, because of their continual use of mobile technologies, are the ideal population to apply these devices.

The mHealth approaches to optimal SUD treatment are those that collect data to either identify or predict substance use, and those that deploy real time interventions to prevent future use. This review article covers the recent literature on wearable and mobile phone app based approaches for the detection and treatment of SUD in adolescents and young adults. We define adolescents (ages 13–17) and young adults (ages 18–24) based on prior work in both SUD- and technology-related research [4,5]. mHealth approaches to prevent SUD in unaffected populations as well as interventions that are solely based on text messages or web-based content (eHealth) have been reviewed extensively elsewhere [6–9].

II. Epidemiology and correlates of SUD in the adolescent and young adult population

Young adults are particularly susceptible to problematic substance use. According to the 2016 National Survey on Drug Use and Health (NSDUH), 8.0 million (23.2%) individuals aged 18 to 25 reported using an illicit substance in the past 30 days [10]. Seven percent of individuals aged 18–25 reported a SUD in the past year: the most common substances used included marijuana, opioids, and cocaine. In a national sample of US adolescents, peak period of heroin initiation was identified at age 17–18 [11].

Risky behaviors and poor impulse control are common characteristics among adolescents and young adults, and intensify the risk for SUD after virtually any substance exposure [12]. Functional MRI studies have suggested that an imbalance between prefrontal impulse control and dopaminergic reward areas underlie the increased risk-taking behaviors seen during youth, and it is well established that developing brains are susceptible to long-term changes from substance use[12]. For example, marijuana use during adolescence has been associated with the development of cannabis dependence, other substance use, cognitive impairment, antisocial behaviors in adulthood, and accelerated onset of mental illness [13–15]. Exacerbating the problem, young adults with SUD are even less likely to seek treatment than those with other psychiatric disorders [16].

III. Potential reach of mHealth among adolescents and young adults

Online connectivity among youth is nearly ubiquitous. In 2015, 92% of adolescents in the US reported going online daily with 24% reporting that they were online "almost constantly"[5]. Prevalence of smartphone ownership has fueled this trend; a majority of adolescents (73%) own or have access to a smartphone, while 92% of individuals ages 18–29 reported owning a cell phone.

A growing body of work suggests new environmental influences on substance use culture from technology immersion. Young adults are increasingly exposed to favorable portrayals of harmful substances and behaviors via digital media [17]. Ubiquitous engagement with social media, susceptibility to peer influences, and cultural normalization of substance use all amplify this effect. However, despite these digital threats, mHealth based interventions represent a promising opportunity for researchers and clinicians to use digital communication to combat these trends.

The popularity of smartphones arises, in part, from the multimodal lines of communication —voice, text, image, video—enabled by mobile technology. A national survey of adolescents age 13–18 years old found that the internet is the primary source of health information among 84% of respondents[18]. The striking uptake of smartphones among adolescents has led to a proliferation of health-related apps, games, and wearable devices targeted to this population, and about a quarter of adolescents report using these types of digital health tools [18]. In addition to being cost-effective and efficient, mHealth may enable researchers to reach a more demographically representative sample including youth that are at particularity high risk [19].

IV. Evolution of mHealth as a tool for SUD assessment and intervention

The growing use of internet-enabled devices in everyday life has fostered the development of an all-encompassing ecosystem of connected smartphones, wearable devices and peripheral internet-connected tools known as the "Internet of Things" (IoT)[20]. Leveraging the interconnectivity of IoT, mHealth investigators have begun to create connections with providers and develop novel IoT based systems that broadly appeal to young people. By engaging patients who are facing threats to sobriety in the locations where these threats are most powerful, mHealth based interventions offer a novel approach for clinicians to treat SUD [21].

The ability of noninvasive mobile devices to collect data allows a combination of detection strategies. Ecological Momentary Assessment (EMA) provides a well-established mechanism to gather self-reported data on craving, cues and substance use, and is made even more effective when integrated into a mobile device [22]. For SUD, mHealth approaches offer the ability to detect episodes of substance use/relapse in real time, with minimal input required from the patient or clinician. For example, the combination of elevated heart rate, increased electrodermal activity (EDA) and decreased skin temperature [23], or characteristic changes in ECG patterns [24,25], can suggest cocaine use or relapse. Transdermal wearables can also detect alcohol in body fluids [26–29], and have the potential to expand the panel of detected substances (see table 1). The increasing sophistication of big data modeling strategies and machine learning algorithms facilitate the acquisition of actionable biometric data and improves the ability of mHealth to detect disease[30,31].

Concurrently, mHealth applications for the diagnosis of disease have created a novel space in which initiation of treatment may occur at the moment of greatest need[32]. The ability to detect acute episodes of substance use, withdrawal, and craving using wearables creates the opportunity for clinicians to deliver targeted interventions in response to these events. Information from a wearable sensor can transmit data wirelessly to a smartphone app, which can in turn trigger timely interventions that respond to detected events, such as craving or overdose, to prevent use or alert medical personnel. The content of these interventions can vary, including video based messages, interactive text messaging, referrals to treatment, or notifications to a support person that a substance use event occurred.

Preliminary studies have shown that patients with SUD are just as likely as healthy controls to engage in mHealth interventions, with similarly high rates of response and acceptability [33,34]. Among patients in SUD treatment programs, access to mobile phones is high (91%) compared to computers (45%) making mHealth advantageous over eHealth approaches [35]. Other studies have noted comparable rates of mobile phone usage in patients being discharged from SUD treatment (85–92%) [36,37].

V. Types of mHealth Studies: Detection and Intervention (Table 1)

Detection of substance use

Studies focusing solely on the detection of substance use employ several methods of quantification. App based real time sampling of an individual's behavior (EMA) can be triggered based on changes in biometrics or geolocation to understand the contextual basis of substance use [22,38]. Alternatively, wearable sensors allow for continuous measurements of physiology or biochemical parameters to signal substance use. Wearable sensors come in a variety of forms, including wrist bands, chest straps and transdermal patches.

The detection of opioid use has been studied with both self-report and physiology based strategies. In 2015, Linas et al reported the use of mobile phone based EMA in participants with a history of intravenous drug use to record daily heroin and/or cocaine use as well as contextual data and cravings surrounding the drug use events [39]. Ninety percent of participants reported at least one drug use event, with a total of 844 reported drug use events over 30 days (N= 109 participants). Distinct contextual situations were associated with episodes of cravings that did not result in use versus episodes of actual drug use. Carreiro et al (2016) also reported the use of wrist mounted wearable sensors to identify physiologic changes of opioid use in 30 participants; decreased motion and increased skin temperature correlated with therapeutic opioid use, and distinct physiologic changes were noted with varying degrees of opioid tolerance [40].

Self-report mechanisms for alcohol detection have been studied extensively, and are typically coupled with interventions (see “Combined Detection/Intervention” below). Biochemical monitoring of alcohol is a newer but promising modality in mHealth[41]. A transdermal alcohol monitoring patch that used perspiration as the analyte was described by Gamella et al in 2014 [29]. In 40 healthy volunteers, the patch showed good linear correlation (r=0.9) with simultaneously measured standard blood alcohol levels (BAL) over 2 hours of continuous measurement. Kim et al (2016) described a wearable, temporary tattoo based alcohol monitoring system that detects alcohol in sweat and subsequently transmits BAL information via Bluetooth connection to a mobile phone app [28]. Their prototype was tested on 9 heathy volunteers, and also showed good correlation with BAL. Other biochemical sensors that include a companion intervention are reviewed below (see “Combined Detection/Intervention”).

Cocaine use is particularly amendable to physiology based detection strategies. Hossain et al (2014) used a chest mounted wearable to measure respiratory rate, ECG, accelerometery, skin conductance and skin temperature to detect cocaine use under laboratory conditions and in natural settings [24]. The wearable transmits data to a mobile phone app, which stores data on identified drug use. Field detection of cocaine use achieved a 93% true positive rate with only a 7% false positive rate. Natarajan et al (2013) described the use of a chest band wearable ECG monitor linked to a smartphone app to detect cocaine use in lab participants (N=6) with Receiver Operative Characteristic (ROC) Area Under the Curve (AUC) of 0.9 both between and within subjects on the best feature predictors [25]. In a subsequent study in 2016, the same investigators described the application of this technique to detect cocaine use in field participants (N=5), which included a mobile phone EMA app to capture episodes of cocaine use[42]. Carreiro et al used wrist mounted wearable sensors to measure cocaine use in 15 participants in natural environments. Increased electrodermal activity (EDA), increased locomotion and decreased skin temperature correlated with episodes of cocaine use. The wearable sensor detected 100% of cocaine use episodes confirmed by self-report and/or urine drug screen, and multiple unconfirmed episodes suspicious for cocaine use[23].

Intervention

Another strategy is to deploy targeted mHealth based interventions for known SUD and related behavioral issues without incorporating a detection strategy. For example, Dennis et al evaluated a mobile phone based EMA/Ecological Momentary Intervention (EMI) in 29 adolescents recently discharged from SUD treatment programs [43]. The authors reported high rates of completion of prompted EMA by adolescents (87%), and lower rates of reported substance use in the next week after EMI was used (32 vs 43%). Gamito et al (2014) reported a randomized controlled trial (RCT) of a video game style mobile app to deliver cognitive stimulation to 54 patients in treatment for alcohol use disorder (AUD), which they hypothesized would improve treatment success [44]. Patients in the treatment arm showed a significant improvement in frontal lobe function tasks compared to controls. This investigator group also used a similar video game based cognitive stimulation program in a group of 14 patients with heroin addiction and noted improvements in multiple dimensions of cognitive performance including frontal lobe functioning [45]. Additional video game based interventions are currently under investigation. Bindoff et al (2016) described the design and development of a smartphone app geared toward smoking cessation called “Quittr” which will be evaluated in a RCT. The app uses a video game approach to embed educational elements, to reward users for accomplishments related to smoking cessation goals and to sustain participation with the app [46].

Combined Detection/Intervention

Many recent mHealth studies have described a combination of substance use pattern detection and intervention. The most popular detection methods used to trigger a targeted intervention in current literature are self-report and GPS tracking, and the main focus to date has been problematic alcohol use. This type of model can eventually become even more powerful by 1) incorporating wearable sensor based physiologic or biochemical detection (as described above) as the source of information and 2) expanding the substances of abuse targeted.

One well studied example is ACHESS (Addiction Comprehensive Health Enhancement Support System)[47,48]. This mobile app includes monitoring tools (GPS tracking to identify high risk areas, and self-reported substance use and craving), educational tools, a panic button (to connect with family/support system), motivational quotes, and a sobriety counter to track progress. Gustafson et al (2014) described a RCT of 349 patients being discharged from alcohol treatment programs who received usual care or usual care plus ACHESS [49]. Participants in the intervention group had significantly less risky drinking days, and were significantly more likely to maintain abstinence at 8 and 12 months follow up. Chih (2014) described various alcohol use profiles among participants in the ACHESS studies, and reported that active participants (those that had the highest level of interaction with the app content) had a trend toward lower risk for relapse after treatment compared to passive participants, but the difference was not statistically significant. This finding highlights the importance of access and engagement with the app for the success of mHealth based strategies[48]. The ACHESS intervention may also be useful for other SUD populations: the investigators intend to trial the app in an opioid dependent population in the near future [50].

A second well studied detection and intervention app also targeted to the AUD population is the Location-Based Monitoring and Intervention for Alcohol Use Disorders (LBMI-A) [51]. Monitoring features of LBMI-A include in-app self-report for tracking alcohol consumption and GPS tracking for at risk locations. Intervention components include educational tools to prevent craving, access support, enhance problem solving skills and stress management, in addition to triggered alerts upon entering a high-risk location. In 2014, a usability study of 28 participants reported these tools as helpful, and participants had a significant reduction in hazardous drinking and drinks per day. In a pilot study of the LBMI-A, the investigators reported that individuals receiving LBMI-A had a large decrease in percentage of heavy drinking days compared to the control group (online educational tool plus bibliotherapy) which resulted in only a moderate reduction in this metric [52].

Other groups have combined self-report with mobile app-based interventions as well. Bertholet (2017) developed a mobile app-based intervention for reducing alcohol consumption [53]. Monitoring capabilities of the app included a self-report alcohol monitoring tool and BAL calculator, while intervention capabilities included personal feedback on alcohol use patterns, a designated driver tool and educational modules. In a pilot study, 130 adults with self-identified problematic alcohol abuse were given the mobile app to use for 3 months. Participants who engaged with the app more than once showed a significant reduction in drinks per week (IRR= .7). Shrier et al (2014) reported a pilot study utilizing a program that combined a brief in person motivational enchantment therapy with a mobile app [54]. The mobile app monitored marijuana use, craving and triggers via EMA and responded with supportive/motivational message content. The study population (N=27) was of youth (age 15–24) with problematic marijuana use who were asked to use the app for two weeks. This study reported 60% protocol completion with overall high user acceptability, and showed a trend toward decreased marijuana use during the intervention and at 3 months follow up.

Many commercially or publically available mobile apps combine the detection plus intervention model to targeted AUD as well. Attwood et al (2017) describe a mixed methods study of a commercially available app (Drinkaware) used to track alcohol use and support alcohol reduction efforts [55]. Monitoring capabilities include self-reported alcohol intake (with tracking capabilities for calories and alcohol volume) and geolocation of user defined “weak spots” (locations where they have trouble regulating alcohol use). Intervention capabilities include goal setting, progress reports, motivational messages based on goals and/or physical location. Over one hundred and nineteen thousand users downloaded the app. App users tended to be “highly motivated” to reduce alcohol consumption, and those who remained engaged (only approximately 5%) with the app reported modest by significant reduction in both total alcohol consumption and binge drinking (approximately 15% and 16% respectively). Feedback from users was mixed, however a consistent theme of desire for more personalized content was evident. Gajecki et al described a study of 1932 Swedish college students randomized to the use of a publically available mobile app (Promillekoll) that provided estimates of BAL based on user entered alcohol consumption data versus a web based version of a similar app versus a control condition of no intervention [56]. Significantly more participants used the mobile app compared to the web based app; however, those in the mobile app group actually showed increased drinking frequency, particularly among male participants. The authors speculate that having the app may have provided a false sense of security, allowing users to drink more. This interesting finding highlights the potential for unintended consequences related to gamification or quantification of substance use.

Currently underutilized, the combination of wearable detection with an intervention strategy has significant promise. In 2017 Barnett et al reported an RCT used a contingency management approach to reduce alcohol consumption using a continuous transdermal alcohol sensor[57]. Thirty participants wore the Secure Continuous Remote Alcohol Monitoring Bracelet (SCRAM) for three weeks. They were randomized to monetary reinforcement contingent upon alcohol abstinence (as detected by the SCRAM device) or yoked non-contingent reimbursement. Transdermal alcohol detection by SCRAM showed good correlation with self-reported use (AUC = 0.79%), and participants in the intervention group had a higher percentage of alcohol abstinent days compared to controls (54% vs 31%) although this did not reach statistical significance.

VI. Challenges to the success of mHealth for SUD

Despite the broad use of mobile devices by an increasingly connected society, challenges remain that must be overcome to realize the full potential of mHealth. Accuracy, security and privacy concerns, in addition to a plethora of unproven interventions threaten advances in mHealth research.

Establishing accurate mHealth based detection strategies poses a unique set of challenges compared to traditional biologic specimen testing. Relying on physiology to identify drug use can make it difficult to differentiate similar classes of drugs (e.g. cocaine versus methamphetamine), or to identify simultaneous use of multiple distinct classes (i.e. polysubstance use). The small sample size of most detection based studies and the lack of a gold standard for identifying drug use in the field also limit the generalizability of this data to the larger SUD population.

Novel mHealth tools pose new concerns regarding data security and patient privacy [58]. Privacy breaches may occur through several methods. First, collection of biometric data, annotations, and even geolocation through mHealth tools may be accessible to close contacts of patients. Discovery of a patient’s use of mHealth—whether by a family member who finds a disease specific app on a patient’s smartphone, or via a bystander who witnesses input of information on a wearable device—are novel avenues in which a patient’s information can be inadvertently divulged.

Perhaps more concerning is potential interference with, and frank alteration of mHealth data. For example, tampering with data collected through a wearable device may be used to describe healthy or unhealthy events. Interpreted by a remote clinician or machine learning protocol, these tampered events may alter the course of treatment in patients. In the context of mHealth-based substance use treatment, alteration of mHealth data to reflect sobriety when an individual may have relapsed can create a false perception of treatment success.

Finally, with the number of commercially available apps and devices that make health claims, rigorous research is needed to separate the effective and evidence based mHealth interventions from those that are not. A content analysis of smoking cessation apps from Abromos et al in 2013 revealed that despite the large number of apps available to consumers, few adhered to any clinical practice guidelines [59]. Penzenstadler et al (2016) performed a content review of 52 commercially mobile apps related to AUD, and noted overall poor quality and low availability of evidence based content [60]. Researchers and clinicians will need to develop tools to systematically evaluate potential interventions before they are adopted clinically.

VII. Future Research

Ongoing work to detect and treat substance use disorders should focus on continuing to integrate mHealth approaches to aid diagnosis, monitoring and treatment [61]. The wealth of wearable device and app options can also lead to device and app fatigue. This may result in disengagement with the mHealth tools, and ultimately poor data from a disorganized mHealth ecosystem. Careful attention is needed to design engaging, easy to use systems that require minimal effort on the part of the user.

Despite the concern for sensor fatigue, validation of each component of an mHealth based toolkit will initially require separate apps and wearable devices and research to identify optimal strategies for each patient and disease process. Unfortunately, no standard for device, operating system or even programming architecture currently exists. Future research may focus on developing a platform agnostic architecture where novel interventions can be programmed in a plug-and-play fashion.

A critically important focus for future work will be adapting mHealth to suit individual needs, creating personalized strategies based on age, gender, severity of SUD, etc. [62]. Ongoing efforts to maintain both clinician and participant engagement will be crucial to the success of mHealth strategies [63].

VIII. Conclusion

Wearable-smartphone combinations provide a powerful toolbox for real world, real time treatment of SUD that is especially suitable for the adolescent and young adult populations. Detection methods include EMA, biochemical testing (e.g. sweat and interstitial fluid based substance detection) and physical/physiologic monitoring (GPS, accelerometery, heart rate, ECG, EDA, skin temperature). Mobile based interventions include interactive apps that provide theory based treatment, support networks (social networks, or direct contact), educational tools, and motivational tools. Numerous studies have demonstrated the capability of these systems to detect various SUD conditions and to deploy interventions. mHealth cannot replace in person addiction treatment, but offers an important adjunct to extend the reach of the treatment team beyond the walls of the clinic and into the patient’s world where threats to sobriety occur. Future research should be geared toward refining the detection capabilities and developing evidence based tools that integrate mHealth based detection and interventions.

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Table 1

Select mHealth studies: Detection and Intervention

Adolescent / Young adult specific	First Author	Year	Text Ref	Type	Description	N	Key Findings
N	Linas	2015	39	Detection	Mobile phone based EMA for detection of drug use & craving	109	• 90% of participants reported drug use with EMA • Distinct environment s detected for drug craving versus drug use episodes
N	Carreiro	2016	40	Detection	Wrist mounted biosensor used to detect physiologic changes with therapeutic opioid use	30	• Opioid use associated with increased skin temperature and decreased locomotion • Characteristi cs of locomotion changes varied based on user opioid tolerance
N	Gamella	2014	29	Detection	Prototype of transdermal sensor for continuous sweat based alcohol detection	40	• Device able to continually measure alcohol content over 2 hours • Strong linear relationship between device reading and BAL
N	Kim	2016	28	Detection	Prototype of wearable, temporary tattoo for sweat based alcohol monitoring with Bluetooth mobile connectivity	9	• Tattoo reliably detected alcohol in sweat • Readings correlated linearly with BAL
N	Hossain	2014	24	Detection	Detection of cocaine use using ECG measurements wearable chest band (Autosense) in lab and field participants	51	• ECG based cocaine detection model with > 90% detection accuracy
N	Natarajan	2013	25	Detection	Wearable ECG chest band sensor for cocaine use in participants	6	• ECG features can reliably detect cocaine use with high accuracy, AUC > 0.9 both between and within subjects
N	Natarajan	2016	42	Detection	Wearable ECG chest band sensor for field detection of cocaine use	5	• Using methods described in Ref 25 applied to field data • Detection accuracy was only slightly lower in field (AUC = 0.81) than in lab (AUC = 0.9)
N	Carreiro	2016	23	Detection	Wrist mounted sensor measuring accelerometer y, skin conductance and skin temperature for cocaine detection in field participants	15	• Wearable sensor detected 100% (N=13) of confirmed cocaine use episodes (based on timeline follow back and urine drug screens). • Sensor detected an additional 12 unconfirmed episodes (possible false positives versus unreported cocaine use)

Adolescent / Young adult specific	**First Author**	**Year**	**Text Ref**	**Type**	**Description**	**N**	**Key Findings**
Y	Dennis	2015	43	Interventio n	Mobile phone based EMA and EMI for youth recently discharged from SUD treatment programs	29	• High rate of substance use by adolescents • When self- initiated EMI was used, lower rates of reported substance use in the next week
N	Gamito	2014	44	Interventio n	RCT of usual care versus usual care plus mobile app based video game to improve cognitive function in individuals being treated for AUD	54	• Significant improvemen t in frontal lobe functioning based tasks in intervention group compared to usual care group
N	Gamito	2017	45	Interventio n	Video game mobile app to improve cognitive function in individuals being treated for heroin addiction	14	• Improvemen t in multiple cognitive domains after app use including frontal lobe function, memory, attention and decision making
N	Gustafson	2014	47	Detection/ Interventio n	RCT of usual care vs usual care plus ACHESS, a mobile app to detect alcohol use (via self- report and GPS tracking) coupled with a suite of intervention tools	349	• Intervention group had less risky drinking days and higher rates of abstinence at 8 and 12 months follow up
N	Chih	2014	48	Detection/ Interventio n	Description of ACHESS use profiles and associated risk of relapse	142	• Users with the highest level of interaction with the content had a trend toward lower risk of relapse to alcohol use
N	Dulin	2014	51	Detection/ Interventio n	Usability study for LBMI-A, mobile app for AUD with self- report and GPS tracking, plus app based intervention	28	• Participants reported the tool as helpful and had a significant reduction in drinks per day
N	Gonzalez	2015	52	Detection/ Interventio n	Pilot study to evaluate LBMI- A (as above) vs online module plus bibliotherapy	54	• LBMI-A group had significantly fewer drinks per week and lower percent heavy drinking days
N	Bertholet	2017	53	Detection/ Interventio n	Smartphone based app with detection capabilities (self-report and BAL calculator) coupled with intervention (feedback on use patterns and educational modules)	130	• Only 77% of participants used the app • Significant reduction in drinks per week in participants who engaged with the app > once
Y	Shrier	2014	54	Detection/ Interventio n	Pilot study for combination of brief motivational interview with mobile app for marijuana using youth. Mobile app combines EMA based detection of use, triggers and cravings and deploys supportive content in response	27	• Participants reported overall high acceptability • Trend toward decreased marijuana use during the intervention and at 3 month follow up visit
N	Attwood	2017	55	Detection/ Interventio n	Analysis of app usage data from a commercially available mobile app (Drinkaware) geared toward reduction in alcohol use. Mobile app combined self- report and GPS detection with goal setting, progress reports and motivational messages	119,713	• High attrition was noted early after first use (within 1 week) • Decreased alcohol consumption among participants who consistently engaged

Adolescent / Young adult specific	First Author	Year	Text Ref	Type	Description	N	Key Findings
N	Gajecki	2014	56	Detection/ Interventio n	RCT of publically available mobile app to track alcohol use (Promillekoll) versus a similar web based app versus no intervention	1929	• Increased overall app use in the mobile app group (vs web based app group) • increased frequency of alcohol use in males in the mobile app group
N	Barnett	2017	57	Detection/ Interventio n	RCT of a ankle mounted transdermal alcohol sensor coupled with contingency management approach to maintain abstinence	30	• Transdermal alcohol detection with the SCRAM device showed high correlation with self- reported alcohol use • Increase in alcohol free days in the contingency managemen t group

NOTES: EMA=Ecological Momentary Assessment; EMI=Ecological Momentary Intervention; BAL=Blood Alcohol Level; SUD=Substance Use Disorder; AUD=Alcohol Use Disorder; GPS=Global Positioning System; RCT=Randomized Controlled Trial; LBMI-A=Location-Based Monitoring and Intervention for Alcohol Use Disorders; ACHESS=Addiction Center for Health Enhancement System Studies