Published in final edited form as:
Curr Addict Rep. 2024 April ; 11(2): 191–198. doi:10.1007/s40429-024-00543-5.

Integrating Alcohol Biosensors With Ecological Momentary Intervention (EMI) for Alcohol Use: a Synthesis of the Latest Literature and Directions for Future Research

Yan Wang[1], **Eric C. Porges**[2], **Jason DeFelice**[2], **Daniel J. Fridberg**[3]

[1]Department of Epidemiology, University of Florida, 2004 Mowry Rd, Gainesville, FL 32610, USA

[2]Department of Clinical and Health Psychology, University of Florida, Gainesville, FL, USA

[3]Department of Psychiatry and Behavioral Neuroscience, The University of Chicago, Chicago, IL, USA

Abstract

Purpose of Review—Excessive alcohol use is a major public health concern. With increasing access to mobile technology, novel mHealth approaches for alcohol misuse, such as ecological momentary intervention (EMI), can be implemented widely to deliver treatment content in real time to diverse populations. This review summarizes the state of research in this area with an emphasis on the potential role of wearable alcohol biosensors in future EMI/just-in-time adaptive interventions (JITAI) for alcohol use.

Recent Findings—JITAI emerged as an intervention design to optimize the delivery of EMI for various health behaviors including substance use. Alcohol biosensors present an opportunity to augment JITAI/EMI for alcohol use with objective information on drinking behavior captured passively and continuously in participants' daily lives, but no prior published studies have incorporated wearable alcohol biosensors into JITAI for alcohol-related problems. Several methodological advances are needed to accomplish this goal and advance the field. Future research should focus on developing standardized data processing, analysis, and interpretation methods for wrist-worn biosensor data. Machine learning algorithms could be used to identify risk factors (e.g., stress, craving, physical locations) for high-risk drinking and develop decision rules for interpreting biosensor-derived transdermal alcohol concentration (TAC) data. Finally, advanced trial design such as micro-randomized trials (MRT) could facilitate the development of biosensor-augmented JITAI.

Summary—Wrist-worn alcohol biosensors are a promising potential addition to improve mHealth and JITAI for alcohol use. Additional research is needed to improve biosensor data analysis and interpretation, build new machine learning models to facilitate integration of alcohol

✉Yan Wang, ywang48@ufl.edu.
Yan Wang and Eric C. Porges are co-first authors.

Conflict of Interest Dr. Fridberg serves as a paid consultant for Click Therapeutics, Inc., on the development of mHealth interventions for substance use disorders.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

biosensors into novel intervention strategies, and test and refine biosensor-augmented JITAI using advanced trial design.

Keywords

Alcohol; Transdermal alcohol biosensors; Just-in-time adaptive intervention (JITAI); Ecological momentary intervention (EMI); Micro-randomized trials (MRT)

Introduction

Excessive alcohol use is a significant public health problem. Excessive alcohol use includes drinking exceeding recommended daily or weekly standard drink limits (i.e., in the USA, consuming ≥ 4 drinks per occasion or > 7 drinks/week for a woman, ≥ 5 drinks per occasion or > 14 drinks/week for a man) [1]. Overconsumption of alcohol is a risk factor for more than 200 diseases and contributes to 3 million deaths worldwide (5.3% of all deaths globally) each year [2]. In the USA, more than 140,000 people die from excessive alcohol use annually [3], and overuse of alcohol costs the U.S. over $249 billion per year in lost productivity and wages. Unfortunately, only a small proportion of those who meet criteria for alcohol use disorder (AUD) receive treatment [4]. The 2020 national estimates from the National Survey on Drug Use and Health (NSDUH) indicated that 11% of adults in the USA had AUD, yet only 0.8% of them received any alcohol treatment [5]. Furthermore, while existing psychosocial and pharmacological interventions for alcohol use have demonstrated efficacy, the effect sizes are often modest [6, 7], and lack of continued care (e.g., relapse prevention) could increase relapse risk [8]. Thus, there is a clear need to refine existing alcohol use intervention strategies and develop new approaches to improve outcomes and sustain behavioral changes achieved during treatment.

Mobile health (mHealth) approaches are often cost-effective and have potential to improve outcomes for individuals with excessive alcohol use or AUD. While precise definitions vary [9], mHealth refers broadly to using mobile devices to monitor health-related outcomes or facilitate health behavior change. Thanks to widespread adoption of smartphone technology (85% of American adults own a smartphone, including over 95% of adults under 50 years of age; [10]), novel mHealth methods for assessment and treatment can now be implemented widely in diverse populations. mHealth interventions for AUD to date often have been delivered via text messaging (SMS) or standalone applications installed on the user's smartphone, with evidence of feasibility but mixed outcomes regarding effectiveness (for reviews, see [11, 12]). The only FDA-approved smartphone application ("digital therapeutic") for substance use disorder (including AUD) to date was the reSET application by Pear Therapeutics, Inc., which combined contingency management and cognitive behavioral therapy approaches to reduce relapse risk. However, Pear Therapeutics filed for Chapter 11 bankruptcy in 2023, and new prescriptions for reSET are not currently available [13]. Another example of applications supporting AUD recovery is the "A-CHESS," standing for Addiction–Comprehensive Health Enhancement Support System [14]. Although these apps have shown some efficacy in helping people with AUD in clinical trials, their use tends to be more short term, suggesting more user-friendly or individualized features may be needed [15].

Smartphones can be further paired with wearable sensors (e.g., smartwatches or fitness trackers) to facilitate data collection and monitoring of health behaviors in individuals' daily lives. These advancements have led to the development of methods that leverage mobile technology for assessment and intervention. In particular, ecological momentary assessment (EMA; [16]) has emerged as a popular method for collecting data on real-world health behaviors in vivo. In the past decade, more EMA studies have used smartphones to measure drinking-related outcomes (e.g., quantity/frequency of alcohol use) in participants' daily lives [17•] or during times when alcohol-related harms are more likely to occur, such as during binge drinking episodes [18]. Additionally, EMA has several advantages over retrospective recall for collecting data on drinking-related outcomes. For example, EMA can measure alcohol use patterns, associated psychological states, and other related outcomes (e.g., drinking-related consequences) in near real time within drinking episodes (e.g., [18, 19]) and may be more accurate than retrospective recall for capturing real-world drinking behavior [20].

The purpose of this brief review is to summarize and synthesize recent developments in mHealth for AUD, with a specific focus on the potential for new alcohol biosensors to enhance ecological momentary intervention (EMI) and just-in-time adaptive intervention (JITAI) approaches. While not intended to be a systematic review, in light of rapid developments and greater availability of new-generation wrist-worn alcohol biosensors from approximately 2018 onward [21•, 22•], we focus our attention here on published research since that time. We also propose future directions for research and applications of alcohol biosensors in the intervention space.

Ecological Momentary Intervention (EMI) and Just-in-Time Adaptive Intervention (JITAI)

As an extension to EMA, ecological momentary intervention (EMI; [23]) is a mHealth approach that offers feedback, interventions, or strategy reminders directly to users via mobile technology (e.g., smartphones via text message or in-app notifications), in their natural environment [24]. In this way, EMI has the potential to extend intervention beyond the clinic to individuals' daily lives. EMI may include an EMA component to gather data on the patient's daily experiences, which are then used to inform individualized and timely feedback, reminders, or other interventions [25]. Further, just-in-time adaptive intervention (JITAI) [26] is a subtype of EMI that delivers "in the moment" support to patients based upon their current behaviors or experiences. Specifically, JITAI aims to provide "the right type/amount of support, at the right time, by adapting to an individual's changing internal and contextual state" [27]. A key distinction between EMI and JITAI is that the JITAI includes ongoing assessment to detect changes in the users' internal state or environment and delivers intervention content in response to this information [24, 27]. Some important components in the design of JITAI include decision points, decision rules, and tailoring variables, which all require information collected in near real time to inform the intervention approach [27]. JITAI uses two broad types of measurement to collect information: active measurement (e.g., EMA self-report) and passive measurement (e.g., a smartphone sensor such as an accelerometer or GPS, or a separate biosensor such as a heart rate monitor or transdermal alcohol biosensor).

Research on JITAI for substance use disorders, including AUD specifically, has increased in the past few years but is still at an early stage. In 2022, Perski and colleagues [28•] summarized the existing literature on JITAI for alcohol use as part of a larger systematic review of JITAI for substance misuse. The authors identified seven eligible studies using JITAI to target alcohol use. Of those, four used active assessments via EMA as the basis of the JITAI, while three incorporated passive measurement using phone-based GPS sensors. In the studies using active assessments, participants reported alcohol consumption or risk factors (e.g., plans to drink, low confidence for abstinence) via the EMA or intervention app which were used to tailor the intervention to the participant's current need. In the passive assessment studies, the real-time GPS location served as the trigger for intervention delivery. Most studies reviewed by Perski et al. [28•] focused on evaluating the feasibility and acceptability of the JITAI and were not sufficiently powered to establish the effectiveness of the intervention for reducing alcohol use per se. Response rates to EMA prompts during the alcohol JITAI were in the moderate-to-high range (67–87%), suggesting that relying upon active measurement (via EMA) of patient experiences or states may limit participant engagement and the effectiveness of this approach. In sum, while JITAI for alcohol use holds promise as an intervention strategy, additional research is needed and there is room to improve these interventions, especially regarding participant engagement and obtaining information on drinking behavior while avoiding excessive participant burden or self-report biases. Presently, wider application/testing and further development of JITAI for AUD may be stymied in part by reliance upon burdensome self-reported EMA approaches to capture real-time data on drinking behavior. Alcohol biosensors may address these issues in part by augmenting JITAI/EMI for alcohol use with objective information on drinking behavior that is captured passively and continuously during users' daily lives. The inclusion of biosensors may allow these interventions to maximize their potential by providing the intervention at times when it is most needed, without requiring the participant to self-report of their drinking behaviors in the moment.

Alcohol Biosensors as a Tool to Enhance EMI and JITAI

Over the past several years, rapid developments in transdermal alcohol biosensor technology have positioned these devices as a promising complement to existing smartphone-based EMI and JITAI. There are two transdermal alcohol biosensors commercially and more widely available to researchers (Table 1). The newer wrist-worn BACtrack Skyn is available at a lower cost and as a less obtrusive alternative to the more expensive and bulkier SCRAM-CAM anklet (AMS, Inc.), which was developed primarily for forensic use [21•, 22•]. Alcohol biosensors detect alcohol use passively by measuring the small fraction (less than 1%) of ingested alcohol that is excreted through the skin, expressed as transdermal alcohol concentration (TAC; [29]). While TAC can provide objective data on alcohol use, the TAC signal lags behind blood or breath alcohol concentration (BAC or BrAC) by 20 min to hours due to individual differences in the time required for alcohol to be metabolized by the body and excreted in sweat [30, 31].

In the past 5 years, multiple reports summarized the design, functionality, validity, feasibility, and usability of new wrist-worn alcohol biosensors [21•, 22•, 32•, 33]. Wang and colleagues [21•, 22•] described wrist-worn alcohol biosensors for research use and their strengths and limitations and provided data from preliminary studies deploying those devices in the field, with an emphasis on potential future applications in research and intervention for AUD. In 2022, Yu and colleagues [32•] conducted a meta-analysis based primarily on laboratory-derived studies and found a large correlation between TAC derived from wrist or ankle biosensors and BAC/BrAC ($r = 0.87$, 95% confidence intervals (CIs) = 0.80, 0.93). Of note, the authors reported that, compared to the SCRAM-CAM anklet, wrist-worn biosensors (the Giner WrisTAS, which is not currently available for purchase, and the Skyn) had significantly smaller lag time between BAC and TAC (mean lag time = 135.8 min for ankle versus 66.4 min for wrist-worn biosensors) and stronger correlations between TAC and BAC/BrAC ($r = 0.82$ versus 0.93, respectively; [32•]). Brobbin and colleagues [33] conducted a systematic review of 22 studies evaluating the acceptability (wearing comfort, social comfort, appearance, and ease of use) and feasibility (device tampering and compliance) of transdermal alcohol biosensors. Most studies in that review evaluated the SCRAM-CAM ($n = 16$), while a smaller number ($n = 8$) used wrist-worn biosensors (some studies used more than one type of sensor). Brobbin et al. [33] concluded that these biosensors are acceptable and feasible and have the potential to monitor alcohol use objectively, with wrist-worn biosensors having some advantages over the SCRAM-CAM in the areas of user comfort, appearance, and overall burden. Taken together, these findings suggest that the newer generation of wrist-worn alcohol biosensors is well-suited for integration into JIATI for alcohol misuse.

Application of Biosensors in Alcohol Interventions

Wearable alcohol biosensors have been included previously as an objective measure of alcohol consumption in prior intervention studies, but little research has incorporated biosensors into EMI/JITAI for alcohol use specifically. Prior studies used data on alcohol consumption from the ankle-worn SCRAM-CAM as a component of contingency management to monitor alcohol use in both healthy volunteers and clinical populations, such as people with HIV [34, 35]. In these studies, participants received daily financial incentives for remaining abstinent from alcohol, with abstinence status determined objectively by TAC recorded from a SCRAM-CAM anklet. Both studies showed significant reduction of biosensor-detected alcohol use in the study sample after the contingency management. Of note, those interventions were not EMI/JITAI as they did not deliver intervention content in real time or during high-risk situations where drinking behavior had occurred or was likely to occur, which could be critical for reducing high-risk drinking and mitigating potential alcohol-related consequences. To our knowledge, only one study has used biosensor data to modify intervention content as part of a JITAI for alcohol use. In the Businelle et al. [36] study, patients with AUD who were experiencing homelessness developed a smartphone-based intervention to deliver personalized treatment messages following each EMA. The SCRAM-CAM biosensor was used as an objective measure of drinking outcome in the intervention development phase, with the TAC data and data from EMA contributing to machine learning algorithms that predicted imminent drinking risk. Tailored messages were pushed to participants based on their self-reported level of risk factors during the EMA. Thus, biosensor data were not included as an active part of the intervention itself but used to inform the development of JITAI in this case. The pilot trial (N = 41) they conducted showed promising effectiveness that participants showed decline in all alcohol use outcomes over the 4-week period and reported high satisfaction with the intervention [37]. The limited application of alcohol biosensors in existing intervention studies may reflect barriers to widespread use of these devices, such as cost, concern about treatment/intervention sustainability, lack of prior data on the utility of these devices in naturalistic settings, the need to provide additional participant training, and limited access to the internet or lack of familiarity with mobile or biosensor technology among patient groups [38]. It should be noted that while the Skyn biosensor (device itself is free with subscription) is less expensive than the SCRAM CAM (device itself costs $1500), researchers will need to consider the potential cost burden over time for each device as both require payment in the form of a monthly monitoring/service fee while in use.

Future Directions for Biosensor-Augmented EMI/JITAI for Alcohol Use

With the expanded use of wrist alcohol biosensors in research, we anticipate that future interventions will incorporate these devices into EMI/JITAI for alcohol use and related problems. As noted above, data derived from transdermal alcohol biosensors will be delayed for 20 min to an hour compared to blood alcohol concentration (BAC) due to physiological factors, i.e., the time required for ingested alcohol to be excreted in sweat. Regardless, transdermal biosensor–derived TAC could serve as the basis for important features of an EMI/JITAI for alcohol use reduction by informing intervention decision points (e.g., identifying places or times of day when drinking is likely to occur so that interventions can be targeted to those places/times) and content (e.g., tailoring messages for high versus low or rapid versus slow levels of alcohol consumption). However, several methodological advances are also needed to address current technical limitations (see Table 1) and advance the field before alcohol biosensors can be fully incorporated into EMI/JITAI.

There is a need for methods to gather and process TAC online during actual drinking events so the data can be incorporated into EMI/JITAI. Current software for wrist-worn alcohol biosensors does not permit real-time “live” monitoring of TAC from the devices. Furthermore, the field has not yet established best practices for processing and interpreting TAC data, which is a significant barrier to integrating these devices into novel interventions. For example, the BACtrack Skyn samples data at a high frequency (once per every 20 s, versus once every 30 min for the SCRAM-CAM), and data from that device are susceptible to noise from exposure to environmental alcohol and participant movement. To derive a signal from Skyn TAC, researchers first need to apply a smoothing and filtering process, but currently, there is no consensus on best practices for this data preprocessing. In 2023, Barnett and colleagues [39] modified the TASMAC Macro that was developed for SCRAM-CAM TAC data into a new version that can process and analyze Skyn-derived TAC data, which could be a potential tool to standardize preprocessing. The Macro automatically smooths Skyn data using a 30-min moving average, detects potential non-compliance by detecting abnormally low temperatures (the threshold can be modified to some extent by the Macro user), identifies potential drinking episodes using a TAC threshold approach, and generates episode summary statistics (e.g., peak TAC, area under the TAC curve, and absorption/elimination rate). However, given the current lack of clearly defined criteria for drinking episode detection and individual differences in TAC across drinkers and episodes, the minimal TAC approach may be prone to false positives [40•]. Additional research and development are needed to refine TAC data cleaning and filtering methods, remove potential sources of environmental noise from the signal (e.g., hand sanitizer use), and improve drinking episode detection. We expect that the development of EMI/JITAI based in part on derived TAC features will accelerate once methods are developed to standardize processing, analysis, and interpretation of TAC data. It should also be noted that TAC readings may additionally be impacted by physiological and environmental factors that vary across individuals and drinking episodes, which creates another challenge for TAC data analysis and interpretation [21•, 22•, 41]. Nevertheless, a 2022 study [42•] showed that features extracted from SCRAM-CAM TAC readings (e.g., area under the curve, rise rate, and peak) were associated with drinking-related consequences in young adult heavy drinkers, indicating that TAC data could be used to develop TAC-based decision rules to inform future EMI/JITAI targeting heavy drinking.

Machine learning algorithms can also be developed to identify risk factors for alcohol use, which could inform EMI/JITAI. For example, sensor data collected from the smartphones of young adults has been used to build predictive models using a variety of factors (e.g., movement, phone screen usage) preceding high-risk drinking [43]. Such models incorporate a feed of information from continuous assessments using built-in mobile phone sensors which could be used to trigger the delivery of a range of interventions. However, while phone sensors can passively collect information to predict alcohol consumption, these data are an indirect measure of drinking behavior. With the new wrist-worn transdermal alcohol biosensors, machine learning algorithms could be developed to predict future TAC values using the current TAC value and the absorption rate to directly measure drinking which can then be used to inform EMI/JITAI. Intervention messages can be triggered when the participant is projected to reach a high-risk drinking level. In 2020, Fairbairn and colleagues [44] have worked to develop machine learning algorithms to predict real-time BAC level from Skyn biosensor–derived TAC. If machine learning models using TAC data are refined to the point where they can be deployed on smartphones, JITAI could be designed to push interventions when estimated BAC reaches a certain threshold to reduce potential harms from high-risk drinking.

To further develop and advance technology-based JITAI for risky alcohol use, future studies may wish to consider a micro-randomized trial (MRT) design [45], in which participants are randomized to different intervention options (e.g., sending a push notification of alert for high-risk drinking level) at each decision point (e.g., when alcohol consumption is indicated by a sustained TAC level over a defined threshold). A MRT design allows researchers to address key questions regarding (1) the causal effect of an intervention option in comparison to its alternatives and (2) whether treatment effects vary according to the individual’s current psychological or physical state, or environmental context. This approach is particularly well-suited for developing effective biosensor-based alcohol JITAI as it provides a systematic way to evaluate important features of the intervention design. For example, using MRT, researchers could assess the relative utility of different intervention components (e.g., sending reminders to individuals about their abstinence goals prior to a drinking episode versus sending text messages with intervention-relevant content in locations where high-risk drinking is likely to occur) and the effects of timing of those components on study outcomes (e.g., prior to the start of a drinking episode versus after a biosensor has detected rising TAC). Regardless of the exact trial design used, future work evaluating biosensor-based alcohol JITAI should also consider the potential moderating effects of demographic or other individual difference variables on intervention outcomes. With such information, biosensor-based JITAI can be fine-tuned to optimize its effectiveness and personalized to deliver relevant content based upon individual characteristics.

Critically, integrating alcohol biosensors into JITAI for alcohol-related problems will require access to biosensor device data in near-real time. This function is not currently supported by existing wrist-worn biosensors. We encourage the manufacturers of these products to develop and make available an application programming interface (API) to allow researchers to access device data and incorporate it into other smartphone applications to facilitate development of new JITAI. Manufacturers of other personal biosensors (e.g., the Garmin fitness tracker) have made APIs available to allow possible incorporation of the devices into EMI via some EMA platforms (e.g., mEMA app by Ilumivu Inc.). Special care must be taken during the development and use of those tools and new technology-based JITAI in general, to follow appropriate human subject and privacy protections so that participants' data are secured.

Conclusions

Recent advances in smartphone and alcohol biosensor technology present exciting new opportunities for researchers and clinicians in the alcohol intervention field. While these tools have advanced considerably in the past 5 years, additional work (e.g., algorithms to reliably detect alcohol consumption from TAC and discriminate heavy versus light drinking events, the development of a software interface to permit smartphone applications to access real-time information from the biosensor and provide feedback to the user) is needed before smartphone and biosensor functionality can be integrated into JITAI for alcohol misuse. Previous research using biosensors as a component of a contingency management intervention for alcohol misuse has produced promising results, and additional studies using the latest generation of wrist-worn alcohol biosensors have shown that these devices are acceptable to participants with good feasibility in the field. Future research is needed to improve the processing, analysis, and interpretation of the wrist-worn alcohol biosensor data, to develop and refine machine learning algorithms for JITAI to build on and to test and refine biosensor-augmented JITAI using advanced trial design such as the MRT.

Funding

This work was supported in part by grants from the National Institute on Alcohol Abuse and Alcoholism R21AA027191 (to YW), P01AA029547 (to YW), R01AA030481 (to YW), P01AA029543 (to YW, ECP), K01AA025306 (to ECP), R21AA029746 (to DJF), and T32AA025877 (to JD).

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Table 1

Main advantages and technical limitations of SCRAM CAM and BACtrack Skyn

Device type	Known advantages	Current technical limitations
SCRAM-CAM	Usability • Tamper-resistant band can be secured to the participant's ankle to prevent removal • Commercially available to researchers • Well-validated by research • Approximately 6-month battery life • Can be worn while showering	Usability • Participants report size/weight/noise level concerns as well as embarrassment (Alessi, Barnett, & Petry, 2017) • Disruptive to physical and social comfort, sleep, exercise, clothing choice (Alessi, Barnett, & Petry, 2017) • Cannot be immersed in water, meaning participants cannot swim or bathe while wearing the device
	Data accessibility • Offers 3 mechanisms for data upload to SCRAM web portal where researchers can manage participants and view data: – Wireless – Landline – Ethernet via SCRAM base station • Can store several weeks of readings	Data accessibility • TAC data cannot be viewed from personal mobile device (no Bluetooth connection) or in real time via its data portal if the data have not been uploaded/transferred • Data are sampled every 30 min so are in relatively low frequency
	Data quality • Includes tamper detection features (e.g., temperature and contact sensors) in addition to TAC sensor to ensure participant compliance	Data quality • May be unreliable for detecting low-to-moderate drinking levels (Barnett et al., 2011)
BACtrack Skyn	Usability • Worn on the wrist • Commercially available to researchers • Is small and resembles an activity monitor or smart watch • Battery life is about 10 days • Can be worn while showering	Usability • Band is not tamper resistant and cannot be locked on participant • Good battery life (~ 10 days) but limited storage capacity (72 h). When storage capacity is exceeded, the oldest data are overwritten • Participants must wear the band properly across the wrist, ensuring good contact with the skin. If not, data quality may be impacted
	Data accessibility • TAC, temperature, and motion data are sampled every 20 s	Data accessibility • Dependent upon a smartphone app to upload data. An iOS-compatible device is required to access data recorded by the Skyn

Device type	Known advantages	Current technical limitations
	• Data are transmitted wirelessly via Bluetooth to an Apple iOS-based device to a secure cloud-based BACtrack data portal	• Data cannot be easily reviewed in real time as an app is required to upload the data from the device for analysis
	Data quality	Data quality
	• Includes temperature and motion sensors in addition to TAC sensor. Can potentially infer whether the device has been properly placed on participants' skin and to distinguish likely periods of wear and non-wear	• Studies have found a wide variation of TAC thresholds, limiting automated detection of drinking versus non-drinking (Ash et al., 2022) • Skyn's thinner membrane may be more susceptible to contaminants that produce acute artifacts, wear and tear, or high humidity/temperature (Ash et al., 2022)