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REVIEW

Technology-mediated just-in-time adaptive interventions (JITAIs) to reduce harmful substance use: a systematic review

Olga Perski[1] | Emily T. Hébert[2] | Felix Naughton[3] | Eric B. Hekler[4,5] | Jamie Brown[1] | Michael S. Businelle[6]

[1]Department of Behavioural Science and Health, University College London, London, UK

[2]University of Texas Health Science Center (UTHealth) School of Public Health, Austin, TX, USA

[3]Behavioural and Implementation Science Group, School of Health Sciences, University of East Anglia, Norwich, UK

[4]Herbert Wertheim School of Public Health and Human Longevity (HWSPH), University of California at San Diego, La Jolla, CA, USA

[5]Center for Wireless and Population Health Systems (CWPHS), Qualcomm Institute and HWSPH, University of California at San Diego, La Jolla, CA, USA

[6]TSET Health Promotion Research Center, Stephenson Cancer Center, University of Oklahoma Health Sciences Center, Oklahoma City, OK, USA

Correspondence
Olga Perski, Department of Behavioural Science and Health, University College London, 1–19 Torrington Place, London WC1E 6BT, UK.
Email: olga.perski@ucl.ac.uk.

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Abstract

Background and Aims: Lapse risk when trying to stop or reduce harmful substance use is idiosyncratic, dynamic and multi-factorial. Just-in-time adaptive interventions (JITAIs) aim to deliver tailored support at moments of need or opportunity. We aimed to synthesize evidence on decision points, tailoring variables, intervention options, decision rules, study designs, user engagement and effectiveness of technology-mediated JITAIs for reducing harmful substance use.

Methods: Systematic review of empirical studies of any design with a narrative synthesis. We searched Ovid MEDLINE, Embase, PsycINFO, Web of Science, the ACM Digital Library, the IEEE Digital Library, ClinicalTrials.gov, the ISRCTN register and dblp using terms related to substance use/mHealth/JITAIs. Outcomes were user engagement and intervention effectiveness. Study quality was assessed with the mHealth Evidence Reporting and Assessment checklist.

Findings: We included 17 reports of 14 unique studies, including two randomized controlled trials. JITAIs targeted alcohol (S = 7, *n* = 120 520), tobacco (S = 4, *n* = 187), cannabis (S = 2, *n* = 97) and a combination of alcohol and illicit substance use (S = 1, *n* = 63), and primarily relied on active measurement and static (i.e. time-invariant) decision rules to deliver support tailored to micro-scale changes in mood or urges. Two studies used data from prior participants and four drew upon theory to devise decision rules. Engagement with available JITAIs was moderate-to-high and evidence of effectiveness was mixed. Due to substantial heterogeneity in study designs and outcome variables assessed, no meta-analysis was performed. Many studies reported insufficient detail on JITAI infrastructure, content, development costs and data security.

Conclusions: Current implementations of just-in-time adaptive interventions (JITAIs) for reducing harmful substance use rely on active measurement and static decision rules to deliver support tailored to micro-scale changes in mood or urges. Studies on JITAI effectiveness are lacking.

KEYWORDS
alcohol, just-in-time adaptive intervention, mHealth, substance use, systematic review, tailoring

INTRODUCTION

With improved mobile hardware, software and computational power, individual-level data on substance use triggers can be collected, processed and actioned in or near real-time. A large body of research using technology-mediated ecological momentary assessments (EMAs) in people's daily lives indicates that lapse risk in people attempting to quit or reduce harmful substance use is idiosyncratic (i.e. it differs between individuals), dynamic (i.e. it fluctuates over time) and multi-factorial (i.e. it is driven by multiple variables, such as urge to smoke, negative affect and contextual cues) [1–7]. For example—highlighting the dynamic and multi-factorial nature of lapse risk—in smokers attempting to quit, experiencing a strong urge to smoke was, on average, associated with 20% greater odds of lapsing near the quit date, with odds increasing by a further 30% one week after the scheduled quit attempt. Negative affect, however, was significantly associated with the odds of lapsing near the quit date, but this association levelled off shortly thereafter [4]. To highlight the idiosyncratic nature of lapse risk, a series of *N*-of-1 observational studies to examine factors associated with day-to-day alcohol consumption in individuals with a history of alcohol dependence found that different psychological and social factors were important for different individuals [7]. Just-in-time adaptive interventions (JITAIs) aim to provide tailored support to users at moments of 'need' (e.g. there is a need for support due to low self-regulatory capacity) or 'opportunity' (e.g. there is an opportunity to act positively in line with one's goals) [8,9]. Due to the idiosyncratic, dynamic and multi-factorial nature of lapse risk in individuals attempting to quit or reduce harmful substance use, JITAIs are poised as particularly suited to the delivery of lapse prevention support.

There is no consensus definition of what a JITAI is; although they typically harness mobile technology to deliver support, the mode of delivery is not necessarily a defining feature. Hardeman and colleagues propose that JITAIs can be defined in terms of three characterizing features: (i) the intervention corresponds directly to a need for support in real-time (e.g. the user is at risk of smoking lapse due to experiencing high levels of stress) or an opportunity to act positively in line with one's goals, (ii) the content or timing of the support is tailored to that real-time need or opportunity (e.g. the intervention is tailored to the most prominent lapse risk trigger, such as stress) and (iii) the support is automatically triggered by the system (e.g. app, website, health-care professional, peer) and not directly by the users themselves [10]. Others have argued that JITAIs can also be user-triggered (e.g. pushing a button within an app or requesting a 'CRAVE' or 'LAPSE' message from an automated text message system) [11]. Nahum-Shani and colleagues propose that JITAIs are defined by their constituent parts, which include (i) decision points (i.e. points in time at which an intervention may be delivered), (ii) tailoring variables (i.e. input used to inform decisions as to when or how to intervene for each individual), (iii) intervention options (i.e. the available change strategies or delivery modes) and (iv) decision rules (i.e. rules that systematically link decision points, tailoring variables and intervention options) [8]. Furthermore, some have highlighted that JITAIs are interventions which consider individual change trajectories over time (e.g. from undesired to desired states), taking into account micro- (e.g. weather, stress), meso- (e.g. seasonality, motivational cycles) and/or macro-scale changes (e.g. life transitions such as becoming a parent, retirement) [8, 12] (see also http://osf.io/n3scx).

A scoping review of JITAIs within addiction science and related study designs (e.g. the micro-randomized trial) has recently been conducted [13]; however, to date, there has been no systematic and comprehensive review of decision points, tailoring variables, intervention options, decision rules, user engagement and intervention effectiveness of current implementations of technology-mediated JITAIs for reducing harmful substance use. Such a review would be useful for informing the development of new JITAIs and the optimization of existing ones. We therefore aimed to address the following research questions, taking an inclusive approach to the definition of JITAIs:

1. What decision points, tailoring variables, intervention options and decision rules are used in current implementations of technology-mediated JITAIs for reducing harmful substance use?
2. Which study designs have been used in the development, optimization and evaluation of JITAIs that aim to reduce harmful substance use?
3. What is the uptake of, engagement with and effectiveness of JITAIs for reducing harmful substance use?

METHODS

Study design

This review was informed by the Cochrane Handbook of Systematic Reviews of Interventions [14] and adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist [15]. A protocol was pre-registered on the Open Science Framework (https://osf.io/e9hcj) and on the international Prospective Register of Systematic Reviews (PROSPERO) (https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42019142019).

Criteria for considering studies for this review

Population

We included studies with participants with harmful substance use, including (but not limited to) tobacco, cannabis, alcohol, cocaine or heroin use. As we aimed to provide an overview of the characteristics of JITAIs, interventions targeting participants of any age, in any setting (e.g. primary care, schools) were included.

Intervention

We included JITAIs designed to reduce harmful substance use (e.g. tobacco, cannabis, alcohol, cocaine, heroin), delivered by any type of technological system (e.g. websites, text messages, apps, wearables). Although we were also interested in capturing JITAIs delivered by non-technological systems (e.g. a family member, peer, health-care professional), our search strategy was not specifically designed for this purpose. We took an inclusive approach and considered an intervention to be a JITAI if the primary sensing and delivery mechanism satisfied the following conditions: (i) the intervention corresponds directly to a need for real-time support or an opportunity to act positively in line with one's goals and (ii) the content or timing of the support is tailored to that real-time need or opportunity [10]. We included systems where the delivery of support was automated and in response to either EMAs delivered at decision points ('active measurement') or location/sensor data ('passive measurement') [8]. We considered an intervention to be a JITAI if the majority of the support it was designed to deliver met our definition. However, a text message intervention in which users could trigger support directly by requesting a 'CRAVE' message but where the majority of the support was not adapted to a real-time need or opportunity did not meet the inclusion criteria for this review. In addition, to distinguish JITAIs from one-off substance use screening and brief advice (sometimes referred to as 'just-in-time interventions', or JITs), we considered an intervention to be a JITAI only if the support was delivered repeatedly over a period of time (i.e. more than once per month). Interventions targeting multiple substances/behaviours were included providing that data could be extracted on the substance use component.

Comparison

Due to the descriptive focus of the review, interventions with any type of (or no) comparator were included.

Outcomes

Included studies had to report at least one of the following empirical qualitative or quantitative outcomes: user engagement (e.g. uptake, use, acceptability, liking) or intervention effectiveness (e.g. reduction in urges, smoking cessation, alcohol reduction).

Study designs

Studies of any design (e.g. qualitative and quantitative studies with data from development work, pilot and feasibility studies, evaluation studies) were included provided that a prototype intervention had been developed. Conceptual or methodological papers with no empirical data (including early user studies without a prototype intervention) were not included. Although we recognize that conceptual papers are helpful for addressing the questions of decision points, tailoring variables, intervention options and decision rules, we were interested in summarizing current implementations of JITAIs in this review.

Search methods for identification of studies

Electronic searches

Electronic and hand-searches were conducted in January 2020. As technology-mediated JITAIs first started to appear in the literature during the second half of the 2000s [16], articles published in or after 2000 were included. Where possible, the language index was set to restrict the search to articles available in English. We searched Ovid MEDLINE, Embase, PsycINFO, Web of Science, the ACM Digital Library, the IEEE Digital Library, ClinicalTrials.gov, the ISRCTN register and the dblp computer science library (https://dblp.uni-trier.de/). We combined search terms related to substance use (e.g. alcohol, tobacco, cocaine), mHealth (e.g. digital interventions, apps) and JITAI features (e.g. just-in-time interventions, adaptive interventions, personalization, tailoring). Search terms were piloted and refined to achieve balance between sensitivity and specificity. An academic librarian was consulted for the validation of the databases and the final search terms. Terms were searched for in titles and abstracts as free text terms, word stems (e.g. smok$) or as index terms (e.g. Medical Subject Headings, Subject Heading Words, Keyword Heading Words), as appropriate. See Supporting information, File S1 for the full electronic search strategy.

Searching for other sources

We used first-order reference chaining and drew on expertise within the review team to identify additional articles of interest.

Data collection and analysis

Selection of studies

Articles identified via the electronic and hand searches were merged with EndNote and duplicate records were removed. The first and second author independently screened (i) titles, (ii) abstracts and (iii) full texts against the pre-specified inclusion criteria. In line with the PRISMA checklist, reasons for exclusion were recorded at the full text stage [15]. Discrepancies were resolved through discussion and by consulting the last author if required.

Data extraction and management

A data extraction form was developed by the first and second authors to extract information on (i) study design (e.g. qualitative study, micro-randomized trial); (ii) delivery setting (i.e. country, immediate delivery context); (iii) participant characteristics (e.g. age, gender, educational attainment, type of substance, level of dependence, mental and physical health comorbidities); (iv) delivery platform (e.g. smartphone app, health-care professional) and, where appropriate, operating system;

(v) whether an existing platform was deployed for intervention delivery; (vi) whether in-house or external developers were used to build the platform; (vii) whether treatment was stand-alone or delivered in adjunct to other support; (viii) payment schedule for participation, if payment was provided (e.g. flat payment, payment per EMA); (ix) intervention options, coded against the Behaviour Change Technique (BCT) taxonomy version 1 [17]; (x) presence of engagement features, as specified in [18]; (xi) type of data used at decision points to trigger real-time support (i.e. 'active' or 'passive' measurement); (xii) tailoring variables (e.g. negative affect, self-efficacy, time of day); (xiii) decision rules (e.g. if–then statements); (xiv) whether the decision rules were static or adaptive over time; (xv) JITAI intervention duration; (xvi) theoretical underpinning of the JITAI (e.g. social cognitive theory); (xvii) user engagement (e.g. uptake, acceptability, liking, use); (xviii) effectiveness (e.g. reduced cravings, reduced frequency and/or amount of substance use); (xix) analytical technique(s) used to analyse the primary outcome data; and (xx) whether any open science tools (e.g. documents on the Open Science Framework or source code on GitHub) were available to enable deeper understanding of the JITAI. Data were extracted by the first author. The second author independently extracted data from a random subset (i.e. 10%) of included studies. Discrepancies were resolved through discussion and by consulting with the last author if required.

Quality appraisal

Given the anticipated diversity of study designs, the mHealth Evidence Reporting and Assessment (mERA) checklist [19] was judged as relevant for assessing the quality of studies, including whether or not formative research and user testing has been carried out and reported, and whether barriers to intervention uptake had been considered. Each checklist item was scored as 'fully reported', 'partially reported' (only some evidence reported) or 'not reported' [19]. The quality appraisal was conducted by the first author, with the second author independently rating a random subset (i.e. 10%) of included studies. Discrepancies were resolved through discussion and by consulting with the last author if required.

Data synthesis

Given the diversity of study designs in the included studies, a narrative synthesis was conducted. Results are presented separately for studies with similar study designs that targeted similar behaviours.

In an unplanned analysis, the first and second authors coded factors that hindered or negatively influenced engagement (i.e. 'barriers') and factors that promoted or positively influenced engagement (i.e. 'facilitators') with JITAIs from qualitative or quantitative data presented in the included papers. We used a combination of deductive and inductive coding, with data coded against Perski and colleagues' conceptual framework of engagement [20], where possible.

RESULTS

Study selection

After removing duplicates, a total of 1047 records were identified through the electronic search. After full text screening, 14 studies (presented across 17 papers) were included in the evidence synthesis (see Fig. 1).

Study and participant characteristics

The majority of studies (10 of 14; 71%) were conducted in the United States, with the remaining studies conducted in the United Kingdom (two of 14; 14%) and Australia (two of 14; 14%) (see Table 1). The identified JITAIs targeted alcohol consumption (seven of 14; 50%), tobacco smoking (four of 14; 29%), cannabis smoking (two of 14; 14%) or a combination of alcohol and illicit drug use (one of 14; 7%).

Study designs deployed were single- or two-arm, non-randomized pilot studies (five of 14; 36%), two- or three-arm pilot/feasibility RCTs (five of 14; 36%), two- or three-arm RCTs (two of 14; 14%) and mixed-methods designs in which the analysis of app usage data was combined with qualitative interviews (two of 14; 14%). None of the included studies reported the use of *N*-of-1 observational or experimental designs, or micro-randomized trial designs.

Studies included a median of 57 participants (range = 15–119 713) who were aged between 15 and 75+ years with a balanced gender distribution (median percentage of female participants = 53%). The majority of studies (nine of 14; 64%) were conducted in the community (including university students and participants recruited via an ongoing observational cohort study or primary care) [21–31], with the remaining studies conducted in secondary care (three of 14; 21%) [32–35], acute care (one of 14; 7%) [36] or in a specialist addiction service (one of 14; 7%) [37]. Studies typically reported inclusion criteria related to the frequency of substance use (e.g. daily or non-daily smoking, recent use of illicit drugs) or a diagnosis of substance use disorder (e.g. alcohol use disorder). Six studies (six of 14; 43%) reported that between 15 and 63% of participants experienced co-occurring mental health issues, including elevated symptoms of depression, anxiety and/or multiple drug use [29, 32–37].

JITAI characteristics

Four studies explicitly mentioned that the JITAI was developed based on theory, such as self-determination theory [37], learning theory [25], the information, motivation and behaviour skills (IMB) model of adherence and social action theory [33] and motivational interviewing and brief intervention theory [28] (see Table 1). We coded 14 BCTs in the JITAIs from the published reports or the accompanying online materials. On average, JITAIs included 2.5 BCTs [standard deviation (SD) = 1.9; range = 1–7]. The most frequently included BCTs were '7.1 Prompts and cues' (14 of 14; 100%), '3.1 Social support

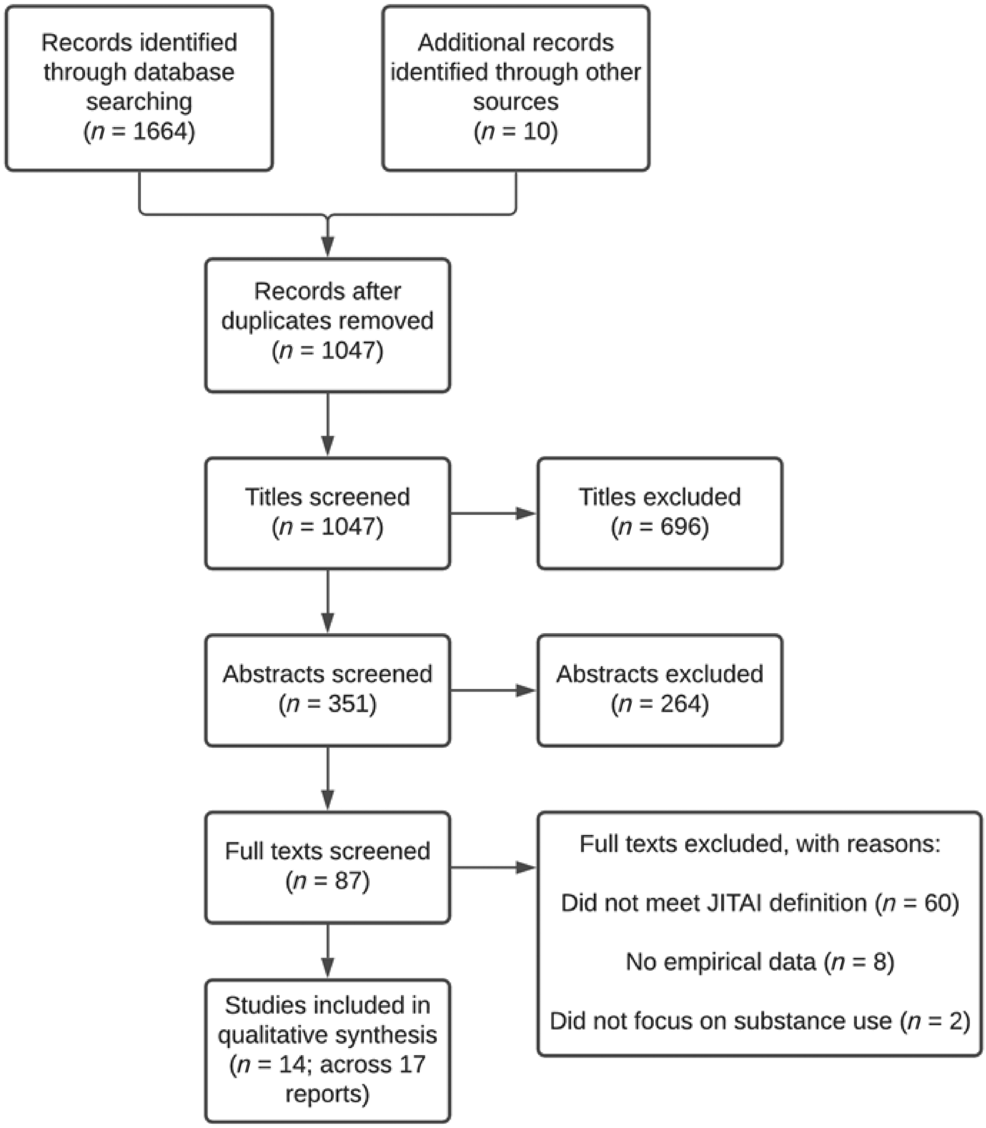

FIGURE 1 Preferred Reporting Items for Systematic Reviews And Meta-Analyses (PRISMA) flow-chart of included studies

(unspecified)' (six of 14; 43%), and '12.3 Avoidance/reducing exposure to cues for the behaviour' (three of 14; 21%). We coded three different engagement features in or pertaining to the JITAIs. For example, if training was provided on how to use the JITAI feature, this was coded as a 'Guidance feature'. On average, JITAIs included 1.9 engagement features (SD = 0.8; range = 1–3). The engagement features deployed were 'Personalization' (14 of 14; 100%), 'Control features' (eight of 14; 57%), and 'Guidance features' (five of 14; 36%).

Intervention durations ranged from 2 weeks to 8 months, although they were typically 4–6 weeks in duration (see Table 2). Where reported (13 of 14; 93%), JITAIs were delivered via smartphones (seven of 14; 50%) [21, 22, 24–26, 29–31], mobile phones (four of 14; 29%) [28,32,33,35,36], hand-held devices (one of 14; 7%) [27] or a combination of mobile phones and hand-held devices (one of 14; 7%) [34]. Three studies reported lending study phones to participants [31, 33, 35]. None of the studies reported that the JITAI was delivered via a non-technological system (e.g. a health-care professional). The majority of JITAIs (12 of 14; 86%) used bespoke software. None of the studies explicitly reported on whether the software used to deliver the JITAI was developed in-house or whether any open science tools were used, such as making the source code accessible to other researchers/developers via a publicly available repository (e.g. GitHub). JITAIs were typically delivered as stand-alone tools, with just over a third of studies (five of 14; 36%) providing adjunct support in the form of face-to-face sessions with a trained counsellor and/or pharmacotherapy [29–31, 34, 35] or treatment as usual (which differed depending on treatment centre) [37]. The majority of studies (nine of 14; 64%) provided monetary incentives for participation, including variable payment contingent upon the number of EMAs/follow-up assessments completed [22–24, 28–31, 34, 35] or a flat payment for study completion [25, 36].

Decision points, tailoring variables and decision rules

JITAIs used two broad types of measurement to determine whether (and if so, what type) of support to deliver: active measurement (i.e. ecological momentary assessments; EMAs) or passive measurement (i.e. the phone's location sensors, including the global positioning

TABLE 1 Characteristics of included studies

Authors (year)	Country	Type of substance	Population	Study design	Sample size
(1) Attwood *et al.* (2017)	United Kingdom	Alcohol	Community dwelling adults	Mixed-methods design	119 713 (usage data); 21 (telephone interviews)
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	United States	Tobacco	Adults recruited from a safety-net hospital-based smoking cessation clinic	Single-arm, non-randomized feasibility study	59
(3) Hébert *et al.* (2020)	United States	Tobacco	Adults recruited from a publicly available smoking cessation clinic	Three-arm, pilot randomized trial	81 (27 in JITAI arm)
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	United States	Alcohol	Community dwelling adults	Two-arm, non-randomized, sequential feasibility study	54 (28 in JITAI arm)
(5) Gustafson *et al.* (2014)	United States	Alcohol	Adults taking part in a residential alcohol use disorder treatment programme	Two-arm RCT	349 (170 in JITAI arm)
(6) Hoeppner *et al.* (2019)	United States	Tobacco	Community-dwelling adults	Single-arm, non-randomized study	32
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	United States	Alcohol and illicit drugs	Adult patients recruited from two non-urban HIV clinics with histories of substance use	Two-arm, pilot RCT	63 (33 in JITAI arm)
(8) Naughton *et al.* (2016)	United Kingdom	Tobacco	Community dwelling adults	Explanatory, sequential, mixed-methods design	15
(9) O'Donnell *et al.* (2019)	Australia	Alcohol	Community dwelling young adults	Two-arm, pilot RCT with post-intervention telephone interviews	45 (25 in JITAI arm)
(10) Shrier *et al.* (2014)	United States	Cannabis	Adolescent patients from two clinics affiliated with a paediatric hospital	Single-arm, non-randomized feasibility study	27
(11) Shrier *et al.* (2018)	United States	Cannabis	Adolescents and young adult patients from an urban children's hospital	Three-arm, pilot RCT	70 (27 in JITAI arm)
(12) Suffoletto *et al.* (2018)	United States	Alcohol	Young adults presenting to an urban emergency department	Single-arm, non-randomized feasibility study	50
(13) Weitzel *et al.* (2007)	United States	Alcohol	College students	Two-arm, pilot RCT	40 (20 in JITAI arm)
(14) Wright *et al.* (2018)	Australia	Alcohol	Young adults recruited from the young adults alcohol study, an observational cohort study	Three-arm RCT	269 (90 in JITAI arm)

JITAI = just-in-time adaptive intervention; RCT = randomized controlled trial.

TABLE 1 (Continued)

Authors (year)	Mean age (SD)	% Female	% Post-18 educational qualifications	Inclusion criterion related to substance use	Mental/physical health comorbidities
(1) Attwood *et al.* (2017)	Range = 17–75+	59%	Not reported	Voluntarily downloading an alcohol reduction app	Not reported
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	52.0 (7.0)	54%	Not reported	Smoking ≥ 5 cigarettes per day	44% had symptoms of depression
(3) Hébert *et al.* (2020)	49.6 (11.9)	50%	Not reported	Smoking ≥ 5 cigarettes per day	Not reported
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	33.6 (6.5)	46%	39%	Meeting DSM-V diagnostic criteria for alcohol use disorder. Participants also had to be drinking a minimum of ≥ 14 standard drinks (females) or ≥ 21 standard drinks (males) on average/week over a consecutive 30-day period in the 90 days prior to evaluation and report ≥ 2 heavy drinking days (4 or more drinks in females, 5 or more in males) in the same 30-day period	Not reported
(5) Gustafson *et al.* (2014)	38.3 (9.5)	39%	8%	Meeting the criteria for DSM-IV alcohol dependence and entering residential treatment	63% used other drugs (e.g. cocaine or other stimulants, opiates) in addition to alcohol; 49% had other mental health issues
(6) Hoeppner *et al.* (2019)	35.0 (12.0)	64%	31%	Non-daily cigarette smokers who smoked at least weekly, but on no more than 25 of the past 30 days	Not reported
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	42.4 (10.0)	37%	35%	Using illicit drugs and/or drinking at levels considered risky in the past 30 days (4 drinks per occasion for women and 5 drinks per occasion for men, OR consuming 8 or more drinks per week for women, and 15 or more per week for men)	> 33% of the sample screened positive for alcohol dependence and nearly 40% screened positive for drug dependence
(8) Naughton *et al.* (2016)	Range = 18–45+	47%	Not reported	Current tobacco smokers	Not reported
(9) O'Donnell *et al.* (2019)	21.4 (4.2)	72%	Not reported	Consuming alcohol on average at least once per week	Not reported
(10) Shrier *et al.* (2014)	Range = 15–24	70%	Not reported	Current cannabis users	33% reported ever been told by a doctor that they have an alcohol or drug problem
(11) Shrier *et al.* (2018)	20.7 (1.9)	60%	Not reported	Current cannabis users	15% had a history of alcohol or drug dependence; 33% had a history of treatment for mental health problems
(12) Suffoletto *et al.* (2018)	22.0 (1.8)	56%	32%	Recent hazardous alcohol consumption based on an alcohol use disorders identification test for consumption (AUDIT-C) score of ≥ 3 for women or ≥ 4 for men and at least 1 binge drinking episode in the past month	25% reported daily tobacco use; 50% reported any cannabis use; 10% reported any opioid use

TABLE 1 (Continued)

Authors (year)	Mean age (SD)	% Female	% Post-18 educational qualifications	Inclusion criterion related to substance use	Mental/physical health comorbidities
(13) Weitzel *et al*. (2007)	19.2 (–)	55%	100%	Consuming alcohol more than once per week	Not reported
(14) Wright *et al*. (2018)	Range = 18–29	48%	Not reported	Recent risky drinking (≥ 5 drinks in a single session in the past 3 months)	Not reported

JITAI = just-in-time adaptive intervention; RCT = randomized controlled trial.

system; GPS). The majority of studies relied on active measurement (10 of 14; 71%) [24, 26–36] (see Table 3). Of the studies that used passive measurement, the majority harnessed the phone's GPS and targeted alcohol consumption [21–23, 37], with one study reporting the use of multiple location sensors (including the phone's GPS) to provide support for smoking cessation [25]. No other sensors or devices were deployed to detect moments of need or opportunity. JITAIs deployed static (i.e. time-invariant) if–then rules, which were typically based on participants entering a given geographical location (sometimes labelled 'weak spots' by the study authors) or whether a particular psychological or contextual variable, such as negative mood, stress, urges or the presence of others who use drugs/smoke, was reported as present (versus absent) or above a pre-specified threshold. A minority of studies from the same research team (two of 14; 14%) [29–31] reported that the if–then rule for triggering support was developed on the basis of lapse risk data from participants in a previous study (i.e. a 'warm start') [2]; the remaining studies did not report deploying data-driven algorithms. None of the included studies considered participant availability or receptivity to just-in-time support in their decision rules. In addition, none of the identified JITAIs adapted the type, frequency or intensity of support according to meso- (e.g. seasonality, motivational waves) or macro-scale changes (e.g. becoming a parent, retirement).

User engagement

Engagement indicators assessed included the response rate to delivered prompts/EMAs (nine of 14; 64%) [24, 26, 28–36], message delivery/receipt (three of 14; 21%) [25, 29, 31], frequency of JITAI use (one of 14; 7%) [22], days of JITAI use (one of 14; 7%) [26] and/or days with receipt of real-time messages (one of 14; 7%) [27] (see Table 3). Where reported, the response rate to prompts/EMAs ranged from 35 to 87%, with low-to-moderate response rates (35–64%) observed in studies targeting cannabis use [34, 35] and moderate-to-high rates (67–87%) in the remaining studies.

Ease of use, message frequency and perceived usefulness were reported as common facilitators to engagement. Where reported, many participants felt that the real-time prompts were quick and easy to complete [26, 28, 34], that the prompt/message frequency was just about right [25, 29] and that the real-time messages were informative and useful for keeping track of and/or reducing substance use [22, 25, 27, 28, 31, 33, 35].

Reported barriers to engagement included technical issues, message frequency and lack of novelty. For example, participants reported location-triggered alerts going off in the wrong place, not always being triggered when supposed to or taking a long time to recognize that the participant had entered a pre-specified location [22, 25]. Participants in one study reported issues with an inconsistent EMA prompting schedule [26]. Some participants felt that they received too many prompts/messages [25, 27, 35] or that the message content was too repetitive [26, 27]. Less frequently-reported barriers to engagement included low perceived personal relevance and

TABLE 2 Characteristics of JITAIs

Authors (year)	JITAI hardware delivery platform	Name of JITAI	Whether JITAI was delivered with existing software	Whether software was developed in-house	Whether treatment was stand-alone
(1) Attwood *et al.* (2017)	Android/iOS smartphone	Drinkaware	Yes	Not reported	Yes
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	Android smartphone	Smart-T	No	Not reported	No; participants had the option to access at least four face-to-face counselling sessions and were offered medication (e.g. nicotine patch, varenicline)
(3) Hébert *et al.* (2020)	Android smartphone (provided to participants)	Smart-T2	No	Not reported	No; participants were offered nicotine replacement therapy (i.e. nicotine patch, nicotine gum)
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	Windows smartphone	LBMI-A	No	Not reported	Yes
(5) Gustafson *et al.* (2014)	Not reported	A-CHESS	No	Not reported	No; the app was offered alongside treatment as usual, but this varied across residential treatment programmes and none offered patients coordinated continuing care following discharge
(6) Hoeppner *et al.* (2019)	Android/iOS smartphone	SmokefreeTXT	Yes	Not reported	Yes
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	Mobile phone (provided to participants)	TEXT	No	Not reported	Yes
(8) Naughton *et al.* (2016)	Android smartphone	Q Sense	No	Not reported	Yes
(9) O'Donnell *et al.* (2019)	iOS smartphone	Minimize	No	Not reported	Yes
(10) Shrier *et al.* (2014)	Mobile phone/PDA	MOMENT	No	Not reported	No; participants received two 1-hour motivational enhancement therapy sessions with a trained counsellor, delivered face-to-face
(11) Shrier *et al.* (2018)	Mobile phone compatible with study software (phones loaned to 55 participants)	MOMENT	No	Not reported	No; participants received two 1-hour motivational enhancement therapy sessions with a trained counsellor, delivered face-to-face
(12) Suffoletto *et al.* (2018)	Mobile phone	TRAC2	No	Not reported	Yes
(13) Weitzel *et al.* (2007)	Wireless hand-held computers	Not reported	Not reported	Not reported	Yes
(14) Wright *et al.* (2018)	Mobile phone	Not reported	No	Not reported	Yes

JITAI = just-in-time adaptive intervention; EMA ecological momentary assessment.

TABLE 2 (Continued)

Authors (year)	JITAI intervention duration	Incentive structure	Theory used to inform development of JITAI
(1) Attwood *et al.* (2017)	Not reported	No payment	Not reported
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	3 weeks	$30 gift cards for completing each in-person assessment visit and based on the percentage of random and daily assessments completed over the study period, with a minimum requirement of 50% assessments completed to receive any payment ($40–120)	Not reported
(3) Hébert *et al.* (2020)	5 weeks	$30 gift card for attending and completing the pre-quit, quit date, and 4-week post-quit follow-up visit and $50 for completing the 12-week post-quit visit. At the 4-week post-quit visit, participants received additional compensation based on the percentage of random and daily diary EMAs that they completed. Those who completed 50% to 74% of all prompted EMAs over the 5-week EMA period received $50, those who completed 75–89% received $100, and those who completed 90% or more received $150	Not reported
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	6 weeks	$60 at each of the baseline and 6-week follow-up assessments. In addition, participants received $5 for each day they completed a daily interview of alcohol consumption and cravings	Not reported
(5) Gustafson *et al.* (2014)	32 weeks	Not reported	A-CHESS was grounded in self-determination theory, which posits that three types of needs (autonomy, competence, relatedness) contributes to an individual's adaptive functioning. The JITAI feature was designed specifically to promote competence
(6) Hoeppner *et al.* (2019)	6 weeks	$35 per online survey (2, 6 and 12 weeks after the quit date), and up to $36 per EMA week (1 week pre-quit and 1 week upon completion of the 6-week survey), with a maximum total of $287 per participant	Not reported
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	12 weeks	Not reported	Information, motivation and behaviour skills (IMB) model of adherence and social action theory
(8) Naughton *et al.* (2016)	4 weeks	£10 shopping voucher for taking part in the qualitative interview	Learning theory and a taxonomy of smoking-related behaviour change techniques
(9) O'Donnell *et al.* (2019)	4 weeks	Not reported	
(10) Shrier *et al.* (2014)	4 weeks	Compensation for travel and remuneration of up to $280 in gift cards, depending on proportion of study activities completed	Not reported

TABLE 2 (Continued)

Authors (year)	JITAI intervention duration	Incentive structure	Theory used to inform development of JITAI
(11) Shrier *et al.* (2018)	4 weeks	Up to $175 with remuneration graded over the study and commensurate with completion of study assessments, including study visits ($15–25) and EMA reports ($10–15 for responding to at least 50% of prompts and $20–25 for responding to at least 80% of prompts)	Not reported
(12) Suffoletto *et al.* (2018)	4 to 12+ weeks (users select time in programme)	$40 upon completion of a 3-month follow-up survey	Not reported
(13) Weitzel *et al.* (2007)	2 weeks	Not reported	Not reported
(14) Wright *et al.* (2018)	12 weeks	$10 per completed event. If all 6 events were completed, a bonus of $20 was given. Participants received $20 for completing the follow-up survey. Participants who completed all 6 events and the follow-up interview received $100 in cash or voucher	Motivational interviewing and brief intervention theory

JITAI = just-in-time adaptive intervention; EMA ecological momentary assessment.

unintended consequences. For example, participants in one study felt that it would have been more useful to receive alerts linked to particular events or when experiencing negative emotions (rather than when dwelling in specific locations) [21]. Unintended consequences of JITAIs included reminding participants of smoking (when they had not been thinking about it) [25] and messages being perceived as guilt-inducing or condescending [27].

JITAI effectiveness

Twelve studies reported on the JITAI's effectiveness (see Table 3), with the majority using linear and/or generalized mixed-effects models that accounted for the nested data structure. Outcome variables assessed were heterogeneous and the majority of studies did not report being sufficiently powered to detect differences in substance use or abstinence rates between groups.

Two medium-sized RCTs found mixed results for alcohol consumption (see Table 3) [28, 37]. Five small-sized pilot RCTs found mixed results for smoking, alcohol consumption and illicit substance use [26, 27, 31, 33, 35]. Five small-sized single- or two-arm non-randomized pilot studies reported mixed results for smoking, alcohol consumption and cannabis use [22–24, 29, 30, 34].

Quality of included studies

None of the 14 studies reported full details for all 16 quality criteria. At least five of 14 studies reported full details on intervention delivery [26, 29, 31, 33, 35] or user feedback [21, 23–27, 29, 31, 33, 34]. Many studies reported insufficient details on either infrastructure, interoperability, usability testing, access of individual participants, cost assessment, limitations for delivery at scale, contextual adaptability, replicability, data security, compliance with national guidelines and fidelity of delivery (see Table 4).

DISCUSSION

This systematic review provides an overview of decision points, tailoring variables, intervention options, decision rules, user engagement and intervention effectiveness of current implementations of JITAIs to reduce harmful substance use. The majority of JITAIs relied on active measurement (i.e. EMAs) to deliver real-time support tailored to micro-scale changes in, for example, mood or urges. Engagement with available JITAIs was moderate-to-high, which may at least in part be related to the receipt of flat or variable payment contingent on the number of EMAs or follow-up assessments completed. The majority of studies deployed single or multiple-arm pilot designs, with two medium-sized RCTs. We found mixed evidence for JITAI effectiveness; however, most studies did not report being sufficiently powered to detect group differences in substance use or did not include a comparator. In addition, many studies reported insufficient detail on the JITAI infrastructure,

TABLE 3 Decision points, decision rules, tailoring variables, user engagement and effectiveness of JITAIs

Authors (year)	Type(s) of data used to trigger real-time support	Decision rule(s) for triggering real-time support	Whether decision rules were static or adaptive	Tailoring variables used to personalize real-time support
(1) Attwood *et al.* (2017)	GPS	If entering a pre-specified geographic location ('weak spot'), then trigger a support message	Static	Not reported
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	EMA	If lapse risk score ≥ 1.0, then trigger a support message. The lapse risk score was calculated as follows: (urge − 3) × 0.2 + (stress − 3) × 0.2 + (cigarette availability − 3) × 0.7 + (interacting with someone smoking [yes = 1; no = 0]) + (recent alcohol use [yes = 1; no = 0]) − (cessation motivation − 3) × 0.2	Static	Negative affect; stress; smoking urge; cigarette availability; motivation to quit. Messages were tailored to the highest rated trigger. Where multiple triggers were equally highly rated, one message was delivered with preference given to negative affect/ stress, smoking urge, cigarette availability and motivation to quit (in the given order)
(3) Hébert *et al.* (2020)	EMA	Same as Businelle *et al.* (2016)	Static	Same as Businelle *et al.* (2016)
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	GPS	If crossing a pre-specified geographic boundary, then trigger alert (auditory and vibration)	Static	Not reported
(5) Gustafson *et al.* (2014)	GPS	If entering a pre-specified geographic boundary, then trigger alert	Static	Not reported
(6) Hoeppner *et al.* (2019)	EMA	If mood = BAD or craving = HIGH, then trigger support message	Static	Mood; craving
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	EMA	If mood = 0–2 (bad mood) or skies = rainy/cloudy/snowy, then trigger support message	Static	Substance use; mood
(8) Naughton *et al.* (2016)	Android Location Services, which uses multiple location sensors including the GPS	If entering or dwelling (defined by Q Sense as 3 hours or more) in a pre-specified geofence, then trigger support message	Static	Geofence-triggered support messages were tailored based on average values of features specific to each geofence, collected during smoking reports (location type, strength of urge, mood, perceived stress, presence of other smokers). Other support messages drew from a pre-populated database that matched the user's 11-item demographics
(9) O'Donnell *et al.* (2019)	EMA	If the user indicates that they are drinking or intend to drink, then trigger support message	Static	Goals (to reduce alcohol use or harm); affect (positive or negative); social context (alone or with others)
(10) Shrier *et al.* (2014)	EMA	If the user reports one of their top 3 triggers for use, desire to use, or	Static	Top 3 triggers for each participant were selected from lists of types of

(Continues)

TABLE 3 (Continued)

Authors (year)	Type(s) of data used to trigger real-time support	Decision rule(s) for triggering real-time support	Whether decision rules were static or adaptive	Tailoring variables used to personalize real-time support
		recent use, then trigger a support message		companions (alone; family; friends, etc.), locations (home, school, work, etc.), activities (work/chores, school/homework, hanging out/socializing, etc.) and feelings (annoyed, anxious, bored, excited, happy, etc.)
(11) Shrier *et al*. (2018)	EMA	Same as Shrier *et al*. (2014)	Static	Same as Shrier *et al*. (2014)
(12) Suffoletto *et al*. (2018)	EMA	If confidence is < 4, then trigger self-efficacy boost message	Static	Willingness to set reduction goal, confidence, drinking behaviour
(13) Weitzel *et al*. (2007)	EMA	If experiencing negative consequences or reporting drinking without consequences, then trigger support message	Static	Negative consequences, self-efficacy, outcome expectancies
(14) Wright *et al*. (2018)	EMA	If–then rule	Static	Plans to eat, location, time, mood, planned drinking, cumulative drinking, planned spending, cumulative spending, adverse events

JITAI = just-in-time adaptive intervention; EMA ecological momentary assessment; IQR = interquartile range.

TABLE 3 (Continued)

Authors (year)	Barriers (−) and facilitators (+) to users' engagement	Summary of users' engagement with JITAI	Analytical technique used for estimation of JITAI effectiveness	Effectiveness of JITAI
(1) Attwood *et al*. (2017)	Low perceived personal relevance (−)	14% of users chose to define a drinking 'weak spot' in week 1. JITAI use rapidly declined over time	Not reported	Not reported
(2) Businelle *et al*. (2016); Hébert *et al*. (2018)	Message frequency (+)	87% of all prompted EMAs were completed. On average, participants received 102.1 (SD = 23.7) automated intervention messages	Generalized linear mixed models	A total of 41% (24/59), 17% (10/59), 31% (18/59), 27% (16/59), 22% (13/59) and 20% (12/59) of participants met biochemically confirmed abstinence criteria at the quit date, week 1, week 2, week 3, week 4, and week 12 follow-up visits, respectively. Messages focused on coping with smoking urges corresponded to significantly greater reductions in urges, as compared with messages that were not tailored to smoking urge ($\beta = -0.62$, $P < 0.001$). Stress-focused messages corresponded to significantly greater reductions in self-reported stress, as compared with messages that were not tailored to stress ($\beta = -0.31$, $P < 0.001$). Messages tailored to reduce easy access to cigarettes corresponded to greater reductions in self-reported cigarette availability compared with messages not specifically tailored to reduce easy access to cigarettes ($\beta = -0.21$, $P < 0.001$)
(3) Hébert *et al*. (2020)	Perceived usefulness (+)	84% of all prompted EMAs were completed. On average, participants received 145 treatment messages	χ^2 tests or analyses of variance	A total of 26% (21/81) of participants were biochemically confirmed abstinent at 4 weeks post-quitting (Smart-T2: 6/27, 22%, QuitGuide: 7/27, 26%, usual care: 8/27, 30%), and 17% (14/81) participants were biochemically confirmed abstinent at 12 weeks post-quitting (Smart-T2: 6/27, 22%, QuitGuide: 4/27, 15%, usual care: 4/27, 15%). There were no significant differences in smoking abstinence between treatment groups at any time-point

TABLE 3 (Continued)

Authors (year)	Barriers (−) and facilitators (+) to users' engagement	Summary of users' engagement with JITAI	Analytical technique used for estimation of JITAI effectiveness	Effectiveness of JITAI
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	Technical issues (−); perceived usefulness (+)	The JITAI feature was accessed 6.0 times on average (SD = 2.1)	Linear mixed models	No results reported specifically for the JITAI feature. The LBMI-A app resulted in a significant increase in percent days abstinent, and a significant reduction in percent heavy drinking days and drinks per week between the baseline assessment and the 6-week follow-up
(5) Gustafson *et al.* (2014)	Not reported	Not reported	Linear mixed models	No results reported specifically for the JITAI feature. Patients in the A-CHESS group reported significantly fewer risky drinking days compared with patients in the control group for the intervention and follow-up period and at months 4 and 12, but not month 8
(6) Hoeppner *et al.* (2019)	Not reported	Most participants reported their mood (84%) or craving (88%) at least once when prompted	Linear mixed models	Abstinence rates were 45% at the 2-week follow-up (7-day abstinence), 56% at the 6-week follow-up (30-day abstinence), and 47% at the 3-month follow-up (30-day abstinence)
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	Lost/stolen hardware (−); lack of time (−); perceived usefulness (+)	The response rate for prompts focusing on substance use was 67%	Mixed effect model	There were no significant differences between groups in days with substance use post-intervention
(8) Naughton *et al.* (2016)	Forgetting (−); technical issues (−); perceived accuracy (+); message frequency (+/−); perceived usefulness (+); unintended consequences (−)	A total of 202 geofence-triggered messages [aggregated mean delivery rate per day of 3.0 (SD 0.8) per participant] were delivered. A total of 1109 support messages were delivered by the app [mean = 85.3 (SD 38.1)]per participant)	Not reported	Not reported
(9) O'Donnell *et al.* (2019)	Lack of novelty (−); technical issues (−); ease of use (+)	Participants responded to 68% of prompts. On average, participants engaged with the app on 22.1 days (SD = 9.7) out of a possible 28 days	Mixed effect models	There was no significant main or interaction effect of time or group on the frequency of risky drinking or alcohol-related harm
(10) Shrier *et al.* (2014)	Ease of use (+); low perceived burden (+)	The response rate for momentary reports was 64% during the baseline week, 50% during the 2 weeks of	Wilcoxon's signed-rank test	The odds of using cannabis following top-3 trigger exposure were reduced by almost 50% at follow-up versus

(Continues)

TABLE 3 (Continued)

Authors (year)	Barriers (−) and facilitators (+) to users' engagement	Summary of users' engagement with JITAI	Analytical technique used for estimation of JITAI effectiveness	Effectiveness of JITAI
		the intervention and 64% during the follow-up week		baseline (OR = 0.54, 95% CI = 0.31–0.95, *P* = 0.03). Compared with baseline, average daily frequency of cannabis use tended to be less during the intervention (RR = 0.78, 95% CI = 0.60–1.02, *P* = 0.07) and at follow-up (RR = 0.73, 95% CI 0.49–1.08, *P* = 0.11). Percentage of days abstinent over the past 30 days increased slightly, but non-significantly, from baseline to follow-up (37.9 versus 47.3%, *P* = 0.13)
(11) Shrier *et al*. (2018)	Message frequency (−); perceived usefulness (+)	A median (IQR) of 35.1% (24.6–60.4%) of the momentary reports and 57.1% (39.3–85.2%) of the diaries were completed	Linear and generalized mixed effects models	There was a significant arm-by-phase interaction effect, with a greater decline in momentary cannabis desire with MOMENT, compared with MET-only. Cannabis use on momentary reports also decreased over the study, with odds of use in the intervention and follow-up phases significantly lower than in the baseline phase (OR = 0.46, 95% CI = 0.28–0.76 and OR = 0.31, 95% CI = 0.19–0.51, respectively). However, the arm-by-phase interaction was not significant
(12) Suffoletto *et al*. (2018)	Not reported	Response rates to EMAs were, on average, 82.3% for the first 4-week intervention block, 75.3% for the second 4-week block and 72.8% for the third 4-week block	Random effects models	All groups, except for those enrolled in the study for +12 weeks, significantly reduced their maximum number of drinks consumed on any weekend day. However, those who selected to enrol for 12+ weeks had lower baseline drinking levels
(13) Weitzel *et al*. (2007)	Message frequency (−); lack of novelty (−); perceived usefulness (+); unintended consequences (−)	12 participants were sent messages on 12–14 of study days, 3 on 9–11 days, and 5 on 5–8 days. Half of the participants reported reading 98%–100% of the messages	Analyses of covariance	Participants in the treatment group reported drinking significantly fewer drinks per drinking day compared with participants in the control group during the study period when responding on the hand-held computer, but not on the pen-and-paper follow-up surveys

TABLE 3 (Continued)

Authors (year)	Barriers (−) and facilitators (+) to users' engagement	Summary of users' engagement with JITAI	Analytical technique used for estimation of JITAI effectiveness	Effectiveness of JITAI
(14) Wright *et al.* (2018)	Competing demands (−); ease of use (+); perceived usefulness (+)	63% of participants signed up for 6 or more events and the majority completed surveys for all 6 events	Random effects mixed models	The JITAI group showed a small but non-significant increase between baseline and follow-up in the mean number of standard drinks consumed at the most recent heavy drinking occasion (mean = 12.5 versus mean = 12.7)

JITAI = just-in-time adaptive intervention; EMA ecological momentary assessment; IQR = interquartile range.

intervention content, development costs and data security. Similar to Hardeman and colleagues' recent review of JITAIs to promote physical activity [10], as research into JITAIs is in its early stages (both in terms of the quality of current implementations and the strength of available evidence), it is premature to comment on the effectiveness of JITAIs for reducing harmful substance use. However, our review highlights important conceptual and empirical gaps for researchers, developers and health-care professionals, as discussed below.

Current state of the field and recommendations for future work

First, there is no consensus definition of what JITAIs are and how to develop them, with a minority of extant studies relying on theoretical predictions or observational/experimental data from prior participants to devise decision points, tailoring variables, intervention options and/or decision rules. The utility of JITAIs designed to reduce harmful substance use will depend largely upon their ability to account for the observed idiosyncratic, dynamic and multi-factorial nature of lapse risk [1–7]; yet current JITAI implementations do not facilitate real-time optimization for individual users. Therefore, prior to investing in large-scale RCTs, we contend that further systematic and creative conceptual and computational work—with insights from the former feeding into the latter and vice versa—is required to make progress on JITAI effectiveness.

Second, although important methodological and statistical advances to support JITAI development, testing and optimization have been made —including the multi-phase optimization strategy, micro-randomized trials, supervised and unsupervised machine learning [38, 39]–few studies identified in our review made use of such innovative approaches. Therefore, researchers, developers and practitioners interested in JITAIs should be supported to adopt relevant new methodological and statistical skills and/or ensure that such expertise is available within multi-disciplinary JITAI project teams.

Third, our review identified two primary ways in which JITAIs determine whether the user is in need of support: active measurement via EMAs or passive measurement, such as via location sensors. Although engagement with EMAs and intervention messages was moderate-to-high across the included studies (indicating that user engagement is not itself a key barrier), payment was typically provided for completing EMAs or follow-up assessments. We therefore need evidence as to whether participants will also engage with EMAs outside controlled study settings where no payment is provided. A move from active to passive sensing of physiological or ecological indicators of lapse risk (e.g. heart rate variability [40,41], step count, weather) is also an important avenue for future research, with potential for reducing user burden and costs associated with financial incentives for completing EMAs. On the other hand, based on available data, the process of completing active measurements, such as EMAs, can help people reflect on their cravings, mood, etc., which may contribute to an enduring learning experience beyond the use of the JITAI itself [42]. There are also important ethical considerations that need to be accounted for when deciding between active versus passive

TABLE 4 Quality appraisal with the mHealth Evidence Reporting and Assessment (mERA) checklist

Authors (year)	(1) Infrastructure	(2) Technology platform	(3) Interoperability	(4) Intervention delivery	(5) Intervention content	(6) Usability testing	(7) User feedback	(8) Access of individual participants	(9) Cost assessment
(1) Attwood *et al.* (2017)	Not reported	Not reported	Not reported	Partially reported	Partially reported	Not reported	Fully reported	Not reported	Not reported
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	Not reported	Partially reported	Not reported	Fully reported	Partially reported	Not reported	Fully reported	Fully reported	Not reported
(3) Hébert *et al.* (2020)	Not reported	Partially reported	Not reported	Fully reported	Not reported	Not reported	Fully reported	Partially reported	Not reported
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	Not reported	Partially reported	Not reported	Partially reported	Partially reported	Not reported	Fully reported	Partially reported	Not reported
(5) Gustafson *et al.* (2014)	Not reported	Not reported	Not reported	Partially reported	Partially reported	Partially reported	Not reported	Not reported	Partially reported
(6) Hoeppner *et al.* (2019)	Not reported	Partially reported	Not reported	Partially reported	Not reported	Not reported	Fully reported	Not reported	Not reported
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	Not reported	Partially reported	Partially reported	Fully reported	Partially reported	Fully reported	Fully reported	Fully reported	Not reported
(8) Naughton *et al.* (2016)	Not reported	Partially reported	Not reported	Partially reported	Partially reported	Not reported	Fully reported	Not reported	Not reported
(9) O'Donnell *et al.* (2019)	Not reported	Partially reported	Not reported	Fully reported	Partially reported	Not reported	Fully reported	Not reported	Not reported
(10) Shrier *et al.* (2014)	Not reported	Not reported	Not reported	Fully reported	Partially reported	Partially reported	Fully reported	Not reported	Not reported
(11) Shrier *et al.* (2018)	Not reported	Not reported	Not reported	Partially reported	Partially reported	Partially reported	Partially reported	Not reported	Not reported
(12) Suffoletto *et al.* (2018)	Not reported	Partially reported	Not reported	Partially reported	Partially reported	Partially reported	Not reported	Not reported	Not reported
(13) Weitzel *et al.* (2007)	Not reported	Not reported	Not reported	Partially reported	Partially reported	Partially reported	Fully reported	Not reported	Not reported
(14) Wright *et al.* (2018)	Not reported	Fully reported	Not reported	Partially reported	Partially reported	Fully reported	Partially reported	Not reported	Fully reported

TABLE 4 (Continued)

Authors (year)	(10) Adoption inputs	(11) Limitations for delivery at scale	(12) Contextual adaptability	(13) Replicability	(14) Data security	(15) Compliance with national guidelines/ regulations	(16) Fidelity
(1) Attwood *et al.* (2017)	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported
(2) Businelle *et al.* (2016); Hébert *et al.* (2018)	Partially reported	Not reported	Partially reported	Not reported	Not reported	Partially reported	Partially reported
(3) Hébert *et al.* (2020)	Partially reported	Not reported	Not reported	Not reported	Not reported	Partially reported	Not reported
(4) Dulin *et al.* (2014); Gonzalez & Dulin (2015)	Partially reported	Not reported	Partially reported	Not reported	Not reported	Partially reported	Partially reported
(5) Gustafson *et al.* (2014)	Partially reported	Partially reported	Partially reported	Not reported	Not reported	Partially reported	Not reported
(6) Hoeppner *et al.* (2019)	Not reported	Partially reported	Not reported	Not reported	Not reported	Partially reported	Not reported
(7) Ingersoll *et al.* (2014); Ingersoll *et al.* (2015)	Partially reported	Not reported	Partially reported	Not reported	Not reported	Partially reported	Partially reported
(8) Naughton *et al.* (2016)	Not reported	Not reported	Not reported	Not reported	Not reported	Not reported	Partially reported
(9) O'Donnell *et al.* (2019)	Not reported	Not reported	Partially reported	Not reported	Not reported	Not reported	Partially reported
(10) Shrier *et al.* (2014)	Partially reported	Partially reported	Partially reported	Not reported	Not reported	Not reported	Not reported
(11) Shrier *et al.* (2018)	Partially reported	Not reported	Not reported	Not reported	Not reported	Not reported	Partially reported
(12) Suffoletto *et al.* (2018)	Partially reported	Not reported	Partially reported	Not reported	Not reported	Not reported	Not reported
(13) Weitzel *et al.* (2007)	Partially reported	Partially reported	Not reported	Not reported	Not reported	Not reported	Partially reported
(14) Wright *et al.* (2018)	Partially reported	Not reported	Fully reported	Partially reported	Not reported	Not reported	Fully reported

measurement: active measurement has the advantage of those being supported by the JITAI being aware of what data are being gathered but comes at the cost of requiring more time and effort, while passive measurement has the advantage of reducing participant burden but risks being more intrusive into a person's life, often without their full awareness or understanding of what information is being gathered about them, for what purpose and how to control or opt out from such tracking. These tensions are not easily solved and likely requires—just like the development of JITAIs themselves—careful consideration of the characteristics of the population being served by the JITAI, their context and other idiosyncrasies. Therefore, the contribution of active versus passive sensing of key variables of interest within JITAIs to their effectiveness (including how to gather high quality data in an ethically responsible manner) needs to be explicitly studied. Although JITAIs developed within academic or clinical settings need to comply with ethical requirements such as clear disclosure of what data are being collected and their intended use, we note that JITAIs are also developed within commercial settings, with different ethical standards (referred to by some scholars as the 'Wild West' of digital health) [43]. A related area is the use of sensors or digital devices for passive detection of key outcomes of interest, including smartphone-enabled carbon monoxide monitors to verify tobacco smoking abstinence [44], gesture recognition software on smartwatches to identify cigarette (or cannabis) smoking behaviour [45], transdermal alcohol sensors [46] or alcohol and cannabis sensors in the form of 'tattoos' and rings [47, 48]. This may simultaneously help reduce user burden and improve confidence in results, yet requires the same careful considerations as discussed above in relation to the passive sensing of physiological or ecological indicators of lapse risk.

Strengths and limitations

The strengths of this systematic review include a comprehensive search of nine medical, psychology, engineering and human–computer interaction databases, substantial team expertise (as indicated by several team members having contributed to papers included in the review), having two reviewers independently screen studies for inclusion, the coding of JITAI content against available taxonomies and conceptual frameworks and a quality appraisal of included studies against the mERA checklist. However, our review also had several limitations. First, the electronic search and paper screening process was challenging due to the lack of a consensus definition of JITAIs and may mean we did not capture all relevant studies. For example, our reliance upon a specific three-part definition to help determine which studies to include meant that we excluded studies with a 'just-in-time' (JIT) reminder at time-points pre-specified by the user (as opposed to tailored support in response to EMAs delivered at decision points or location/sensor data) [49, 50]. Second, we decided against including conceptual or methodological papers without any empirical data due to our focus on current implementations of JITAIs. However, such papers may have provided additional insight into JITAI decision points, tailoring variables and decision rules, and the types of study designs that are useful for devising these. Third, although we consider the use of a quality appraisal tool a strength of the review, it was challenging to judge the quality of included studies due to insufficient reporting, particularly with regard to the infrastructure required to run JITAIs (e.g. specific hardware, software, size of message banks) and intervention options.

CONCLUSIONS

JITAIs for reducing harmful substance use tend to rely upon active measurement and static decision rules to deliver real-time support tailored to micro-scale changes in mood or urges. Evidence from large-scale studies on JITAI effectiveness is lacking. There is a need for further conceptual work on what JITAIs are and how to develop them, methodological and statistical training for researchers and developers and research examining ethically responsible use of passive sensors for detecting variables of interest.

DECLARATION OF INTERESTS

O.P., F.N. and J.B. are unpaid members of the scientific committee for the Smoke Free app. J.B. has received unrestricted research funding from pharmaceutical companies (Pfizer and J&J) who manufacture smoking cessation medications to study smoking cessation. M.B. is an inventor of the Insight mHealth Platform, which was used to develop the Smart-T2 app. He receives royalties related to the use of Insight. E.T.H. and E.B.H. have no conflicts of interest to declare.

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AUTHOR CONTRIBUTIONS

Olga Perski: Conceptualization; formal analysis; investigation; methodology; writing - original draft. **Emily Hébert:** Conceptualization; formal analysis; investigation; methodology; writing - review & editing. **Felix Naughton:** Conceptualization; methodology; writing - review & editing. **Eric Hekler:** Conceptualization; methodology; writing - review & editing. **Jamie Brown:** Conceptualization; methodology; writing - review & editing. **Michael Businelle:** Conceptualization; methodology; writing - review & editing.

ORCID

Olga Perski https://orcid.org/0000-0003-3285-3174
Emily T. Hébert https://orcid.org/0000-0001-5922-164X
Felix Naughton https://orcid.org/0000-0001-9790-2796
Eric B. Hekler https://orcid.org/0000-0002-7434-0775

Jamie Brown https://orcid.org/0000-0002-2797-5428
Michael S. Businelle https://orcid.org/0000-0002-9038-2238

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SUPPORTING INFORMATION

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