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REGULAR ARTICLE

Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support

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Abstract
Background The just-in-time adaptive intervention (JITAI) is an intervention design aiming to provide the right type/amount of support, at the right time, by adapting to an individual's changing internal and contextual state. The availability of increasingly powerful mobile and sensing technologies underpins the use of JITAIs to support health behavior, as in such a setting an individual's state can change rapidly, unexpectedly, and in his/her natural environment.
Purpose Despite the increasing use and appeal of JITAIs, a major gap exists between the growing technological capabilities for delivering JITAIs and research on the development and evaluation of these interventions. Many JITAIs have been developed with minimal use of empirical evidence, theory, or accepted treatment guidelines. Here, we take an essential first step towards bridging this gap.
Methods Building on health behavior theories and the extant literature on JITAIs, we clarify the scientific motivation for JITAIs, define their fundamental components, and highlight design principles related to these components. Examples of JITAIs from various domains of health behavior research are used for illustration.
Conclusion As we enter a new era of technological capacity for delivering JITAIs, it is critical that researchers develop sophisticated and nuanced health behavior theories capable of guiding the construction of such interventions. Particular attention has to be given to better understanding the implications of providing timely and ecologically sound support for intervention adherence and retention.

Keywords Just-in-time adaptive intervention · Support · Mobile health (mHealth) · Health behavior

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Introduction

An emerging intervention design, the *just-in-time adaptive intervention* (JITAI) holds enormous potential for promoting health behavior change. A JITAI is an intervention design that adapts the provision of support (e.g., the type, timing, intensity) "over time to an individual's changing status and contexts," with the goal to deliver support "at the moment and in the context that the person needs it most and is most likely to be receptive" [1]. Increasingly powerful mobile and sensing technologies underpin this intervention design [2]. They allow us to monitor the dynamics of an individual's internal state and context in real time and offer support flexibly in terms of time and location [3]. JITAIs are increasingly being used to support health behavior changes in domains such as physical inactivity [4], alcohol use [5], mental illness [6], smoking [7], and obesity [8]. Despite JITAIs' increasing use and appeal, research on their development and evaluation is in its early stages. Many JITAIs have been developed with little empirical evidence, theory, or accepted treatment guidelines [9].

To close the gap between the growing technical capabilities to deliver JITAIs and an understanding of their scientific underpinnings, it is important to clarify why JITAIs are needed and how their objectives differ from those of other intervention designs. This will help scientists build the empirical basis necessary to develop efficacious JITAIs and decide whether a JITAI is warranted in a particular setting [10]. Further, JITAI development requires multidisciplinary effort, involving clinicians, behavioral scientists, engineers, statisticians, computer scientists, and human-computer interaction specialists. A unified lexicon can help to foster communication across diverse perspectives and facilitate better collaboration and scientific exchange [2]. Finally, because JITAIs are multi-component interventions, it is important to clearly define the components that comprise them, so that investigators can attend to the utility of each component. Investigating the effectiveness of each component and how well different components work together is critical in the process of optimizing a multi-component intervention [11].

In this article, we clarify the scientific motivation for JITAIs, define their key components, and highlight important design principles relevant to these components. We also discuss empirical, theoretical, and practical challenges for constructing efficacious JITAIs. We ground our discussion by providing examples of JITAIs from various domains of health behavior research. Table 1 provides a summary of key terms and definitions.

Examples of JITAIs

JITAIs have been implemented and pilot tested in several domains of health behavior change. For example, FOCUS [15] is a smartphone behavioral intervention that provides illness management support to individuals with schizophrenia. FOCUS prompts individuals three times a day (via auditory signals and visual notifications) to assess their status in five target domains: medication adherence, mood regulation, sleep, social functioning, and coping with hallucinations. Once signaled, individuals can engage or ignore the prompt. If they engage, the system launches a brief assessment. When an assessment indicates that the individual is experiencing difficulties, FOCUS recommends self-management strategies to ameliorate the type of difficulties the individual endorsed; otherwise, FOCUS provides feedback and positive reinforcement. No intervention is offered if the individual ignores the prompt.

ACHESS [5] is a JITAI for supporting recovery from alcohol use disorders. It provides 24-7 access via smartphone to a wide variety of supportive services, including computerized cognitive-behavioral therapy, web-links to addiction-related websites, and information on alcohol-free events in their community. Global positioning system (GPS) technology tracks when an individual approaches a high-risk location, namely a location that the individual pre-specified as a place where s/he regularly obtained or consumed alcohol in the past (e.g., favorite bar). If the individual approaches a high-risk location, ACHESS sends an alert to the individual asking him/her if s/he wanted to be there; otherwise, no alerts are delivered.

Finally, SitCoach [16] is a JITAI for office workers in which messages encouraging activity are delivered via a smartphone. Software on the worker's computer records uninterrupted computer time via mouse and keyboard activity. If 30 min of uninterrupted computer time occurs, the smartphone delivers a persuasive message to raise the individual's awareness of his/her sedentary behavior and encourage a walking activity; otherwise, no messages are delivered. SitCoach does not deliver a message if the individual received a message in the past 2 hours, even if s/he exceeds the computer activity threshold during that time.

Motivation for Just-in-Time Adaptive Interventions

Various scientific fields have used different terms to describe interventions that adapt the provision of support to an individual's changing internal and contextual state. These include dynamic tailoring [17], intelligent real-time therapy [18], and dynamically and individually tailored ecological momentary interventions [19]. Here, we use the term JITAI because it integrates two concepts: "just-in-time" and "adaptive." Attending to these concepts sheds light on the motivation underpinning these interventions as well as the components comprising them.

In various scientific fields, including manufacturing [20] and education [21], the term "just-in-time support" is used to describe an attempt to provide the right type (or amount) of support, at the right time [22], namely neither too early nor too late [23]. The motivation for this approach is grounded in the idea that *timing* plays an important role in determining whether support provision will be beneficial. Timing is defined as "the moment (a static reference point in time) at which a phenomenon, process, or part of process starts or finishes" [24]. Timing onset and offset demarcates a *state* that reflects the particular condition(s) that someone or something is in at a particular point or period of time [24]. Here, the concept of timing is largely event-based, in that the answer to the question "when is the right time?" is defined by events or conditions (e.g., when the individual approaches a high-risk location) rather than by clock time (e.g., at 2 pm). Such events/conditions are unexpected—they repeat irregularly, in a manner that cannot be fully predicted [25]. For example, it is

Table 1 Key terms and definitions

Key term	Definition
Intervention design	The approach and specifics of an intervention program.
Just-in-time support	Attempts to provide the right type of support, at the right time, while eliminating support provision that is interruptive or otherwise not beneficial
Individualization	The use of information from the individual to select when and how to intervene.
Adaptation	A dynamic form of individualization, whereby time-varying (dynamic) information from the person is used repeatedly to select intervention options over time.
Just-in-time adaptive intervention (JITAI)	An intervention design aiming to provide just-in-time support, by adapting to the dynamics of an individual's internal state and context. JITAIs operationalize the individualization of the selection and delivery of intervention options based on ongoing assessments of the individual's internal state and context. A JITAI includes 6 key elements: a distal outcome, proximal outcomes, decision points, intervention options, tailoring variables, and decision rules.
State of vulnerability/opportunity	A period of susceptibility to negative health outcomes (vulnerability) or to positive health behavior changes (opportunity).
Distal outcome	The ultimate goal the intervention is intended to achieve; usually a primary clinical outcome such as time to drug use/relapse or physical activity level.
Proximal outcomes	The short-term goals the intervention is intended to achieve. Proximal outcomes can be mediators, namely crucial elements in a pathway through which the intervention can impact the distal outcome, and/or intermediate measures of the distal outcome.
Decision points	Points in time at which an intervention decision must be made.
Tailoring variables	Information concerning the individual that is used for individualization (i.e., to decide when and/or how to intervene).
Intervention options	Array of possible treatments/actions that might be employed at any given decision point. This might include various types of support, from various sources, different modes of support delivery, various amounts of support or different media deployed for support delivery.
Decision rules	A way to operationalize the adaptation by specifying which intervention option to offer, for whom, and when (i.e., under which experiences/contexts). The decision rules link the intervention options and tailoring variables in a systematic way.
Intervention engagement	A "state of motivational commitment or investment in the client role over the treatment process" [12].
Intervention fatigue	A state of emotional or cognitive weariness associated with intervention engagement [13].

impossible to anticipate exactly when the individual will approach a high-risk location. Hence, ongoing monitoring of the individual is required in order to identify when these events/conditions occur (i.e., when support is needed).

The right time to provide support is determined by the theory of change that is guiding support provision, namely how and why a desired change is expected to unfold over time in a particular context [26]. The flip-side of providing the right type of support at the right time is providing nothing when the time is wrong and never providing the wrong type of support [27]. This operationalizes the notion of eliminating waste, namely any activity/action that absorbs resources (e.g., time, effort) but adds no value to, or even disrupts the desired process [28].

Adaptation operationalizes how the provision of just-in-time support will be accomplished [29, 30]. Adaptation is defined as the use of ongoing (dynamic) information about the individual to modify the type, amount, and timing of support [31]. To provide support just-in-time, the adaptation requires monitoring the individual to decide (a) whether the individual is in a state that requires support; (b) what type (or amount) of support is needed given the individual's state; and (c) whether providing this support has the potential to disrupt the desired process.

In the context of health behavior interventions, the use of mobile technology to deliver just-in-time support is rooted in theoretical and practical perspectives suggesting that states of vulnerability to adverse health events, as well states of opportunity for positive changes, can emerge rapidly (e.g., over a few days, hours, minutes, even seconds [32–34]); unexpectedly (i.e., in an irregular manner [35]); and outside of standard treatment settings (for review, see [36]).

States of Vulnerability and States of Opportunity

Theories that focus on preventing adverse health outcomes, such as stress-vulnerability [37] and relapse prevention [38] theories, highlight the importance of properly addressing states of vulnerability, namely periods of heightened susceptibility to negative health outcomes (e.g., unhealthy eating, heavy drinking). The emergence of a vulnerable state is a dynamic process in which stable and transient influences interact. Stable factors refer to enduring predisposing influences, including both internal (e.g., personality, genetics) and contextual (e.g., neighborhood safety, unemployment) factors that increase the odds that a person will experience an adverse health outcome at some point in his/her life. In turn, transient influences precipitate a transition in vulnerability from latent (subthreshold) to manifest. Transient precipitating influences can be both internal (e.g., how the person is feeling) and contextual (e.g., location) [37, 38]. A vulnerable state can emerge rapidly, unexpectedly, and in the individual's natural environment, as s/he encounters circumstances that precipitate his/her longstanding vulnerability [39]. These precipitating circumstances can vary between people and within a person over time [32]. The JITAI aims to contain the vulnerable state and return the condition of vulnerability to latent.

One example of a JITAI that aims to address a vulnerable state is FOCUS, which was motivated by evidence suggesting that transient difficulties play an important role (along with stable factors such as biological predisposition) in the course and outcomes of schizophrenia. Specifically, difficulties such as fatigue and interpersonal conflict precipitate a transition to a state of vulnerability that signifies the patient's increasing risk for full symptomatic relapse and illness exacerbation. These difficulties can emerge rapidly, unexpectedly, and outside of standard treatment settings. Further, these difficulties can take different forms across individuals or even in the same individual over time. For example, psychotic episodes might be triggered mainly by states of fatigue for some individuals and by interpersonal conflict for others. Moreover, the individual may be susceptible to relapse because s/he is experiencing sleep difficulties at one time, and at another time because s/he forgot to take his/her medication. Hence, FOCUS aims to provide the type of support needed to help the individual cope with the difficulties s/he is experiencing, at the right time to break the link between these precipitating circumstances, the emergence of the vulnerable state, and its progression into full symptomatic relapse.

JITAIs are also motivated by the importance of capitalizing on states of opportunity, namely periods of heightened susceptibility to positive health behavior changes (e.g., healthy eating, physical activity) [33, 34]. For instance, health behavior maintenance perspectives emphasize the importance of anticipatory coping [40]—a dynamic process involving ongoing anticipation of difficulties and timely execution of the right strategy to prevent and/or minimize temptation (e.g., a dieter keeping healthy food in the refrigerator [39, 41]). Health behavior motivation theories suggest that it is important to break long-term health behavior goals into short-term, specific, and achievable sub-goals; monitor progress; and provide relevant, timely feedback and guidance [35, 42]. Learning and cognitive theories emphasize the role of shaping (i.e., identifying and immediately reinforcing successively improving approximations of the target behavior [43, 44]) and teachable moments (i.e., natural opportunities for learning and improvement [45, 46]) in the acquisition of a new skill. Overall, these perspectives emphasize that timely provision of intervention scaffolds and prompts can capitalize on short-term natural opportunities to improve health outcomes. For example, SitCoach is motivated by evidence suggesting that the occurrence of 30 min of uninterrupted computer use constitutes a teachable moment that can be framed to raise an office worker's awareness of his/her sedentarism. To capitalize on this opportunity, when 30 min of sedentary behavior occurs, SitCoach provides feedback and persuasive messages to encourage the worker to be more active.

Because states of vulnerability and/or opportunity can emerge rapidly, unexpectedly, and ecologically (i.e., in the individual's natural environment), it is usually infeasible to use in-person (face-to-face) approaches to identify the time when support is needed and to deliver the right type of support in a timely manner. Hence, the provision of just-in-time support in health behavior interventions relies heavily on the use of mobile and wireless devices (mHealth) [47]. The widespread use of technologies including smartphones, laptops, and tablets enables individuals to access or receive interventions anytime and anywhere [48]. Moreover, the portable nature of wearable and ubiquitous computing sensors (e.g., wearable activity monitors, smartwatches), mobile-phone-based sensing (e.g., accelerometry, GPS), digital footprints (e.g., social media interactions, digital calendars), and low-effort self-reporting (e.g., ecological momentary assessment [EMA]) make it possible to monitor individuals continuously and hence to know when and why a state of vulnerability/opportunity emerges [49]. Even so, new challenges to intervention adherence and retention arise.

New Challenges to Intervention Adherence and Retention

Newly recognized challenges to intervention adherence and retention concern the use of mHealth to address states that emerge rapidly, unexpectedly, and ecologically [19]. First, because states of vulnerability/opportunity can occur repeatedly over time, providing support at the right time might suggest frequent delivery of interventions [50]. Second, addressing these states often requires the delivery of interventions in a real-life setting where multiple demands compete for the individual's time and effort. Finally, to reduce costs and other barriers to treatment (e.g., availability of therapists, stigma), many mHealth interventions include minimal or no support from clinicians or coaches (e.g., [51, 52]). This introduces unique challenges to the extent that supportive accountability (i.e., "implicit or explicit expectation that an individual may be called upon to justify his/her actions or inactions" [53]) is enhanced by the felt presence of another human being [53].

Indeed, various studies demonstrate the law of attrition [54] in mHealth interventions, showing that individuals use mHealth resources only a few times before abandoning them [55, 56], even when they paid for these resources [57]. For example, in a randomized control trial, Laing and colleagues [58] compared a popular publically available app for weight loss with usual care for overweight patients in a primary care setting. Although individuals reported liking the app, use dropped sharply after the first month. For example, the median number of logins was eight in the first month and one in the second month; the number of individuals who actually used the app dropped by 64 % from month 1 to month 6. Hence, JITAIs in mobile health are also motivated by the need to accommodate relatively rapid changes in key mechanisms underlying intervention adherence and retention.

Intervention engagement and intervention fatigue are two important mechanisms that affect adherence and retention. Intervention engagement is defined as a "state of motivational commitment or investment in the client role over the treatment process" []. Intervention fatigue (i.e., burnout) is defined as a state of emotional or cognitive weariness associated with intervention engagement [13]. Empirical and theoretical evidence suggests that both mechanisms are important in intervention adherence and retention [14], and both might ebb and flow over the course of treatment as a function of aspects related to the intervention, the individual, and the context [13,]. For example, King and colleagues [] conceptualize intervention engagement as a multifaceted affective, cognitive, and behavioral state that ebbs and flows over time due to factors related to the intervention (e.g., how treatment is presented and delivered), the individual (e.g., attitudes towards self and treatment), and the context (e.g., work/family demands). Heckman and colleagues [13] conceptualize intervention fatigue as a cognitive and emotional state that fluctuates over time as a function of the interplay between intervention burden (i.e., the demands of an intervention in terms of time and effort), the general demands on the individual (e.g., daily life tasks related to work and family), the capacity of the individual in terms of general resources (e.g., attention, mood), and illness burden (i.e., symptoms such as pain, craving).

Building on these ideas, and consistent with the notion of waste elimination, various perspectives in supportive communication and ubiquitous computing [59–61] emphasize the need to provide just-in-time support only when the person is receptive. Here, *receptivity* is defined as the individual's transient ability and/or willingness to receive, process, and utilize just-in-time support; receptivity is a function of both internal (e.g., mood) and contextual (e.g., location) factors [50]. For example, in FOCUS, support was not offered if the individual ignored the prompt for self-report (i.e., s/he is not receptive). The underlying assumption is that providing support when the person is not receptive will not be beneficial and may even have negative implications on engagement with the intervention and intervention fatigue [61, 62]. Receptivity might change rapidly in the course of a day [61], and what constitutes receptivity depends on the type (i.e., content, media employed for delivery), amount, and timing of support provided [63]. For example, if a person is in a meeting s/he might be receptive to an intervention delivered via a text message, but not receptive to a phone call. When it is raining, a person might be receptive to a recommendation to exercise indoors, but not receptive to a recommendation to walk outside.

Summary of JITAI Definition and Scientific Motivation

A JITAI is an intervention design that employs adaptation to operationalize the provision of just-in-time support, namely to provide the right type (or amount) of support, at the right time, while eliminating support provision that is not beneficial. The use of mobile health (mHealth) in this setting is motivated by the need to address states of vulnerability for adverse health outcomes and/or capitalize on states of opportunity that emerge rapidly, unexpectedly, and ecologically. These states can vary between individuals and over time within an individual. Hence, addressing and/or capitalizing on these states in a timely manner requires continuous, ecological monitoring of an individual's internal state and context to identify when and how to intervene. Advances in portable and pervasive technologies make it possible to continuously monitor individuals, as well as the timely delivery of support "in the wild." However, given the rapid, unexpected, and ecological nature of these states, as well as the law of attrition [54] in mHealth interventions, JITAIs in mobile health are also motivated by the need to address relatively rapid changes in mechanisms underlying adherence and retention.

Notice that the definition above emphasizes that the adaptation in a JITAI is employed by the intervention itself rather than by the target individual. In other words, decisions concerning when and how to provide support are based on the intervention's protocol. This intervention-determined approach is based on evidence suggesting that individuals are often unable to recognize when states of vulnerability and/or opportunity emerge [64, 65] and initiate the type of support needed to address these states in a timely manner [66, 67]. Hence, a JITAI employs adaptation to actively address these states of vulnerability and/or opportunity. We distinguish this from participant-determined approaches that make an array of supportive resources available for the target individual to decide when and what type of support to initiate.

Components of a JITAI

JITAIs are adaptive interventions. An adaptive intervention is an intervention design in which intervention options are adapted to address the unique and changing needs of individuals, with the goal of achieving the best outcome for each individual [68]. Existing frameworks for the design of adaptive interventions [31] highlight four components that play an important role in designing these interventions: (1) decision points, (2) intervention options, (3) tailoring variables, and (4) decision rules. Below, we describe each of these components and how they might be employed in a JITAI. Figure 1 includes a conceptual model of JITAI components.

Decision Points

A decision point is a time at which an intervention decision is made. Given the nature of the conditions JITAIs in mobile health attempt to address and the capabilities of modern technology, intervention decisions are made much more rapidly than in standard adaptive interventions. For example, in FOCUS, intervention decisions were made following each random prompt for self-report. An intervention was not necessarily provided following every random prompt: if the individual ignored the prompt (i.e., s/he was not receptive), no intervention was offered. Table 2 includes other examples of decision points in JITAIs. In general, the decision points in a JITAI might occur (a) at a pre-specified time interval (e.g., the location of a recovering individual is passively monitored every minute to detect if/when s/he is approaching a high-risk location [5]); (b) at specific times of day (e.g., at 2 pm) [73], or days of the week [70]; or (c) following random prompts [15].

Intervention Options

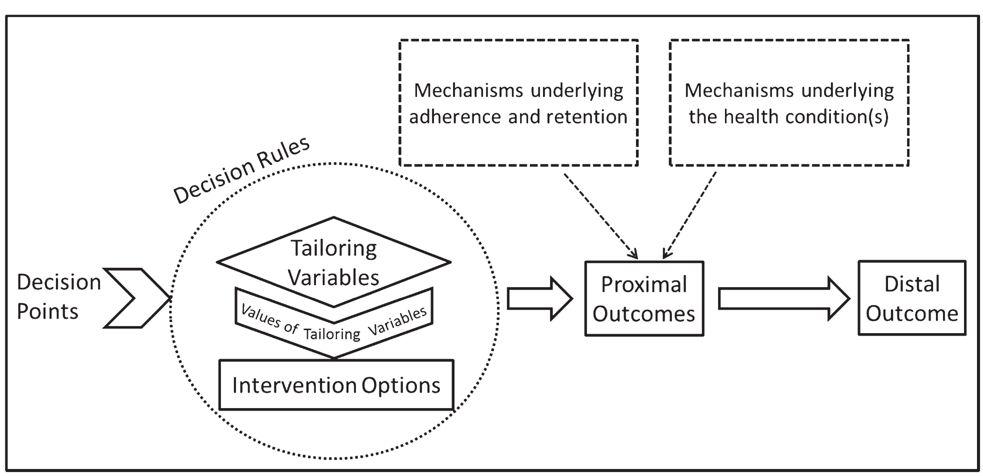
Intervention options are an array of possible treatments or actions that might be employed at any given decision point. In JITAIs, these include various types of support (e.g., information, advice, feedback), sources of support (e.g., smartphone, therapist), amounts of support (i.e., dose/intensity), or media employed to deliver support (e.g., phone calls, text messaging). For example, intervention options in FOCUS included both recommendations of self-management strategies, as well as feedback and positive reinforcement. In a JITAI, intervention options are designed to be delivered, accessed, and used in a timely and ecological manner. The term *ecological momentary interventions* (EMIs) is often used to describe intervention options that can be delivered and employed rapidly, as people go about their daily lives [19].

Tailoring Variables

A tailoring variable is information concerning the individual that is used to decide when (i.e., under what conditions) to provide an intervention and which intervention to provide. For example, in ACHESS, the tailoring variable is an individual's distance from a high-risk location. In a JITAI, the collection of tailoring variables is flexible in terms of the timing and location of assessments. This flexibility enables timely individualization of intervention options to conditions that might change rapidly, unexpectedly, and ecologically.

Tailoring variables in a JITAI can be obtained via active assessments, passive assessments, or both [77]. *Active assessments*, also known as EMAs, are self-reported and hence require engagement on the part of the individual [78]. For example, in FOCUS, participants were prompted three

Fig. 1 Conceptual model of JITAI components



times a day to self-report the status of their difficulties. *Passive assessments* are those that require minimal or no engagement on the part of the individual. For example, in ACHESS, the mobile phone passively monitors the individual's location. This information is used to determine when to send an alert.

Decision Rules

The decision rules in JITAIs operationalize the adaptation by specifying which intervention option to offer, for whom, and when. In other words, the decision rules link the intervention options and tailoring variables in a systematic way. There is a decision rule for each decision point. For example (see Table 2 for additional examples), a decision rule similar to those used in ACHESS but simplified for expository purposes might be of the following form:

If distance to high-risk location $\leq S_0$

Then, IO = [Provide an alert]

Else if distance to high-risk location $>S_0$

Then, IO = [Provide nothing]

Notice that a decision rule includes the values (levels, thresholds, ranges) of the tailoring variable that determine which intervention option should be offered. In the above example, S_0 is the value of distance to high-risk location (the tailoring variable) that determines whether an alert should be offered (if distance $\leq S_0$), or not (if distance $>S_0$). In other words, S_0 specifies when (i.e., the conditions under which) an intervention should be offered. Next we discuss design principles that are important for constructing effective decision rules in JITAIs.

Design Principles for JITAIs

We discuss design principles and considerations aimed at maximizing the *effectiveness* of the JITAI; that is, the ability of the JITAI to achieve the desired distal outcome(s) when implemented in a real-world setting. The distal outcome is conceptualized as the ultimate goal the intervention is intended to achieve; it is usually a primary clinical outcome, such as weight loss, drug/alcohol use reduction, or increase in average activity level. All the design principles discussed below should be guided primarily by the distal outcome targeted by the JITAI.

The Role of Proximal Outcomes

Proximal outcomes are the short-term goals the intervention options are intended to achieve; they can be measured shortly after the intervention is provided, with the aim of gauging whether the intervention is on track in achieving its objectives [79]. As we discuss below, identifying and clearly defining the proximal outcomes can help scientists select appropriate decision points, tailoring variables, and intervention options and formulate effective decision rules. Proximal outcomes are often mediators, namely critical elements in a causal pathway through which the intervention options are designed to impact the distal outcome [79]. For example, JITAIs aiming to prevent adverse health outcomes often focus on mediators that mark the emergence of a vulnerable state. Such markers can be in the form of transient conditions that precede an adverse health outcome, such as mood symptoms (e.g., anxiety, dysphoria) in a JITAI aiming to prevent symptomatic relapse in individuals with schizophrenia [15]. Proximal outcomes can also be intermediate measures of the distal outcome. For example, JITAIs aiming to promote the adoption and maintenance of healthy behaviors often target proximal outcomes that capture short-term progress towards an ultimate health behavior goal (e.g., daily step count in a JITAI aimed at increasing average daily step count over the study duration [80]).

In many cases, there are multiple pathways through which the intervention can impact the distal outcome [81]. In these cases, intervention scientists might select multiple proximal outcomes to be targeted by the JITAI. For example, consider a JITAI for improving eating habits as the distal outcome. Suppose this intervention is designed to target two proximal outcomes: (1) momentary food craving, selected to mark a state of heightened vulnerability for unhealthy eating; and (2) engagement with (operationalized in terms of using) an intervention that is offered to help reduce snack food cravings. Note that this example includes two forms of proximal outcomes: the first is a mechanism that underlies the health condition, and the second relates to intervention adherence/retention. Below, we elaborate on the inclusion of mechanisms that underlie intervention adherence/retention as proximal outcomes in a JITAI.

Proximal Outcomes Related to Intervention Adherence and Retention

To prevent poor adherence to and/or abandonment of JITAIs, it is important that intervention scientists consider proximal outcomes pertaining to intervention engagement and intervention fatigue [82]. These proximal outcomes might be behavioral (e.g., accessing and using the intervention), cognitive (e.g., perceiving the intervention as useful), or affective (e.g., trust in the intervention) []. When selecting proximal outcomes pertaining to engagement, it is important to specify the extent and duration of intervention engagement required in order to achieve the distal outcome. For example, certain interventions require long-term engagement (e.g., a JITAI

Table 2 Examples of decision rules in JITAIs

Example	Decision rule	Decision point	Tailoring variables	Intervention options
Substance abuse intervention based on composite risk assessment	At random EMA prompt If composite substance abuse risk $\geq R_0$ Then, IO = [recommend intervention] Else if composite substance abuse risk $<R_0$ Then, IO = [encouraging message]	Random prompt [15, 51]	Composite risk [69]	Recommend intervention *OR* encouraging message [15, 70]
An individual does not access intervention within M minutes	At *M* minutes after random EMA prompt If composite risk $\geq R_0$ and intervention use in past *M* minutes = NO Then, IO = [message encouraging intervention use] Else if risk $<R_0$ or intervention use in past *M* minutes = YES Then, IO = [provide nothing]	*M* minutes after random prompt [71]	Composite risk [69]; Intervention use in past *M* minutes [72]	Message encouraging intervention use *OR* provide nothing [72]
Physical activity intervention using passive assessments of step count	At 4 pm If current accumulated step count $<P_0$ Then, IO = [recommend exercise] Else if current accumulated step count $\geq P_0$ Then, IO = [encouraging message]	Specific time of day [73]	Current accumulated step count [74]	Recommend exercise [75] *OR* encouraging message [74]
Responding to passively assessed risky location, using active assessments of urge	Every 3 min, If location = close to a liquor store, Then, If self-report urge $\geq U_0$ Then, IO = [send alert to sponsor] Else, if self-report urge $<U_0$ Then, IO = [recommend an intervention] Else, if location = not close to a liquor store Then, IO = [provide nothing]	Pre-specified time interval [5]	Passively assessed location [5]; self-reported urge [51]	Alert sponsor [5] *OR* recommend an intervention [15] *OR* provide nothing [5]
An individual ignores request for assessment	At *M* minutes following a random prompt If EMA completion = NO Then, IO = [TXT encourage EMA completion] Else if EMA completion = YES Then, IO = [provide nothing]	*M* minutes following random prompt [71]	EMA completion [76]	Text encouraging EMA completion *OR* provide nothing [76]

IO intervention option, *EMA* ecological momentary assessment, *TXT* text message

designed to support HIV medication adherence), whereas others require relatively short-term engagement (e.g., a JITAIs designed to prevent smoking lapses in the weeks immediately after quitting).

There are a number of proximal outcomes that potentially reflect intervention fatigue. One concerns cognitive overload, namely experiences of excessive mental demands that impair the ability to remember goals or think clearly about necessary actions [83]. Another is habituation, namely objective decline in physiological and/or behavioral response to an intervention over repeated exposures [84]. A third involves negative emotions, such as boredom (a negative affective state involving lack of interest in and difficulty concentrating on a given activity [85]), as well as other negative emotions, such as anger and disappointment, that reflect emotional exhaustion [86] and intervention fatigue [87].

Interestingly, while the connection between engagement and fatigue has received little systematic research in intervention science, empirical evidence in the area of occupational health psychology indicates that engagement and fatigue are two distinct, yet related concepts that share certain antecedents and consequences [88] and that influence each other in a complex way [89]. In some instances, signs of poor behavioral engagement, such as ignoring intervention prompts, signal intervention fatigue [90], as when the effort needed for repeated use of intervention materials leads to mental exhaustion. On the other hand, the motivational aspects of engagement have the potential to prevent or attenuate intervention fatigue. For example, optimism and trust in the intervention can increase its perceived value and the resources that the individual allocates to bear the demands of the intervention. Analogously, interventions that succeed in fulfilling core psychological needs (e.g., curiosity; discussed below under intervention options) might keep the individual engaged despite any mental weariness caused by intervention demands [13, 91].

Given the reciprocal nature of the link between intervention engagement and fatigue, and given that both play an important role in intervention adherence and retention, we recommend that scientists attend to both concepts when selecting intervention options as well as proximal outcomes. Even though research in organizational and social psychology provides extensive information on both phenomena [92], future research should continue to uncover processes related to engagement and fatigue in the context of behavioral interventions in general and JITAIs in particular to inform the selection of proximal outcomes in a JITAI. Attention should also be given to the measurement of intervention engagement and fatigue given the multifaceted nature of these constructs. Human-computer interaction (HCI) frameworks provide useful guidelines [93], emphasizing that various assessment tools, including self-reports (e.g., affect), physiological sensors (e.g., eye movement tracking to measure visual attention), and intervention usage patterns (e.g., the number of features used in a mobile application), should be combined to capture the emotional, cognitive, and behavioral dimensions of user engagement and fatigue.

Decision Points

When selecting decision points, the first consideration should be given to how often meaningful changes in the selected tailoring variable(s) are expected to occur. Here, changes are considered meaningful if they have implications for which intervention option should be recommended; such changes often represent entry into and exit from a state of heightened vulnerability or a state of opportunity. To clarify this, consider the example decision rule above, where S_0 is the value of distance from a high-risk location (the tailoring variable) that determines whether an alert should be offered (if distance $\leq S_0$), or not (if distance $>S_0$). Here, meaningful changes in the tailoring variable would occur if an individual's distance from a high-risk location reduces to a point S_0, or increases above this threshold. The former indicates entry into a vulnerable state, which requires an intervention to prevent alcohol use (the proximal outcome); the latter indicates exit from this state, so that an alert is not needed.

If distance from a high-risk location is expected to change in a meaningful manner every minute, then there might be a decision point every minute. Alternatively, if meaningful changes in the tailoring variable are expected to occur every 30 min, then there might be a decision point every 30 min. The choice of the time interval between decision points can have a dramatic impact on the ability of the adaptation to achieve its goals. Important opportunities for intervention might be missed if the timing of the decision points is not aligned with how often meaningful changes in the tailoring variable(s) are likely to occur.

When the tailoring variable is measured via active assessments, considerations of assessment burden may lead to less frequent decision points. For example, the selection of decision points in FOCUS (i.e., at random prompts three times/day) was intended to balance empirical evidence and theories suggesting that meaningful changes in mood symptoms (e.g., depression and anxiety) among individuals with schizophrenia are likely to occur rapidly (e.g., every few minutes) with considerations of burden (as well as quality of measurements) that might result from asking the individual to self-report too frequently [15]. On the other hand, in ACHESS, meaningful changes in an individual's location were expected to occur rapidly, and the passive measurement of location ensured minimal burden. Therefore, the decision points are at very small intervals in time (i.e., as often as 1 min, depending on how close the individual is to the high-risk location).

Intervention Options

The intervention options included in a JITAI should be theoretically and empirically driven, and they often target proximal outcomes. Intervention options designed to impact mechanisms that underlie the health condition, such as markers of state vulnerability or short-term clinical progress, are often developed on the basis of multiple health-behavior and coping theories (see [94] for a full review). Although intervention options targeting proximal outcomes related to adherence and retention might benefit from being based upon theories concerning intervention engagement and fatigue [82], this rarely occurs. Hence, we elaborate below on design considerations for these intervention options.

Intervention Options Targeting Engagement and/or Fatigue

Research in occupational health psychology provides a useful framework for disentangling design considerations that primarily concern engagement from those that primarily concern fatigue. This line of research (see [92]) suggests that while engagement and fatigue are related, engagement can be prompted primarily by efforts to fulfill basic psychological needs, such as the needs for autonomy, relatedness, and competence, whereas intervention fatigue can be prevented and ameliorated primarily by attending to the demands imposed on the individual in terms of time and effort (also referred to as intervention burden; see [13]). These ideas are echoed in recent conceptualizations of engagement and fatigue in the context of behavioral interventions [13,].

To promote engagement, various strategies can be used in JITAIs to design intervention options that fulfill basic psychological needs. For example, competence, which concerns individual feelings of efficacy, challenge, and curiosity [95], can be promoted by providing immediate feedback or rewards [96]; by ensuring that intervention options can be readily incorporated into and used in the context of the individual's daily living activities [57, 97]; and by ensuring that intervention options maintain an optimal level of challenge to generate sufficient interest yet avoid frustration or failure [98].

Relatedness, which concerns feelings of being connected to and cared about by others [99], can be promoted by facilitating supportive social interactions (e.g., creating online communities [100]). Autonomy, namely experiencing an internal perceived locus of causality or the self-endorsement of one's action [101], can be promoted by facilitating user agency though participation (e.g., incorporating user preferences in intervention options [102]). Throughout, literature in the area of persuasive computing can be used to guide the development of intervention options that fulfill basic psychological needs by using games, augmented reality, and digital avatars in the form of personal coaches and assistants [103].

To address intervention fatigue, various strategies can be employed to minimize the emotional, cognitive, and physiological demands JITAIs impose on an individual (see [13]). For example, to minimize cognitive overload, it is important to develop intervention options that are intuitive and easy to navigate [6] and that include content that is brief and clear [104]. This is particularly important when the target population has less education, impaired cognitive functioning, and/or less experience with computerized and mobile devices [6].

Varying of the form, presentation, and timing of content delivery is a useful strategy for dealing with both engagement and fatigue [105]. For example, instead of delivering the same content multiple times, the JITAI might draw from a "bank" that includes various forms of relevant content [106]. Additionally, the JITAI might vary the type of media employed or the type of signal (e.g., alerts, pings) used to engage the individual with the content [107]. Enhancing novelty and allowing mental rest introduces variability that can fulfill basic psychological needs (e.g., curiosity), while minimizing boredom, habituation, and general loss of energy [91]. A related strategy involves the explicit inclusion of a *provide nothing* intervention option in a JITAI—an intervention option that provides no intervention at a decision point. This intervention option can be incorporated into the decision rules to address conditions where the provision of support may have negative effects on intervention engagement and fatigue. This includes situations in which the person is unreceptive, as well as conditions in which support is not needed (e.g., because the person is doing well). A "provide nothing" option can also be used to address situations in which the provision of certain types of just-in-time support might be unsafe or unethical (e.g., audibly prompting the person to interact with a message on the phone when the person is driving a car; for more details see [50]).

Tailoring Variables

In this section, we discuss selection of tailoring variables in a JITAI, measurement of the tailoring variables in a JITAI, and missing data on tailoring variables.

Selection of Tailoring Variables

Tailoring variables should be selected based on evidence (practical, clinical, theoretical, and/or empirical) indicating that a particular variable is useful for making intervention decisions. By "useful" we mean that the variable (e.g., food craving) can be used to identify specific conditions (e.g., high food craving) in which individuals are likely to benefit from one intervention option (e.g., prompting a craving-reduction imagery intervention [108]) as opposed to another (e.g., provide nothing) in terms of affecting the proximal outcome (e.g., daily unhealthy snacking).

The selection of tailoring variables should also be guided by the proximal outcomes. In JITAIs targeting proximal outcomes that mark the emergence of a vulnerable state (e.g., alcohol craving), useful tailoring variables are typically those that help identify conditions that represent heightened susceptibility that precede the selected proximal outcome(s) (e.g., approaching a location associated with past alcohol abuse; [5]); in JITAIs targeting proximal outcomes in the form of short-term health-behavior progress (e.g., daily step count), useful tailoring variables are typically those that help identify conditions that represent heightened opportunity for short-term improvement (e.g., the person has been sedentary for 30 min; [75]).

As discussed earlier, JITAIs are often designed to influence more than one proximal outcome, in which case different tailoring variables may be considered for different proximal outcomes. Note that the intervention options required to influence each proximal outcome might differ as well. As a simple example, assume that an intervention scientist is developing a JITAI to produce weight loss (distal outcome) by reducing the number of unhealthy snacking episodes per day (proximal outcome). To maximize intervention adherence/retention, the scientist aims to minimize a second proximal outcome, intervention fatigue. To address the former, a different encouraging message would be offered at the end of each day depending on the number of unhealthy snacking episodes during that day (tailoring variable). In the case of the later, a *provide nothing* intervention option would be used when information about the individual indicates that s/he is not receptive (tailoring variable); this includes when s/he ignores a prompt.

In many cases, it is reasonable to use the proximal outcome as a tailoring variable. In the example above, the individual's current number of snacking episodes (tailoring variable) is used to individualize the intervention options so as to reduce subsequent snacking episodes (proximal outcome). This is motivated by the notion that information about the proximal outcome at a given time point is useful in identifying conditions that represent heightened susceptibility for adverse consequences, or heightened opportunity for positive changes, in terms of the proximal outcome at later time points/periods (e.g., experiencing a large number of snacking episodes on a given day is associated with increased odds of experiencing a large number of snacking episodes in the following day). In general, the decision rules in a JITAI can use information about previous or current values of a proximal outcome to individualize the intervention options. However, tailoring variables are not limited to the proximal outcomes targeted by the intervention. To clarify, assume the intervention scientist from the example above also decides to offer a craving-reduction imagery intervention when the person experiences high food craving (tailoring variable) in order to reduce the number of snacking episodes the individual experiences per day (proximal outcome). Here, the tailoring variable differs from the proximal outcome.

Measurement of Tailoring Variables

When using active assessment to measure tailoring variables, it is helpful to carefully consider the dynamic theories that informed the selection of the tailoring variables. Suppose an investigator constructs a JITAI using emotion-regulation intervention options to reduce unhealthy snacking and decides to use active assessment of momentary negative affect as a tailoring variable. In this setting, negative affect is conceptualized as a dynamic, fluctuating, state construct, with meaning and operationalization that differ from the more static construct of trait negative affect [109]. Active assessment of a dynamic construct can be challenging. For example, individuals may skim over or even ignore parts of an instrument that is presented several times daily [110], possibly reducing measurement reliability and validity. Potential adverse effects related to the response burden of repeated assessment must be balanced against the need to measure the construct frequently enough to obtain an accurate picture of the dynamic process underlying mood state changes.

Passive assessment of tailoring variables is becoming more feasible as sensors of various kinds become more sophisticated and cost-effective. Smartphones include a wide range of sensors (e.g., accelerometer, camera), which can be used to measure the individual's state and context [111]. Capitalizing on these smartphone sensors and other types of sensors (e.g., ECG, galvanic skin response sensors (see also Sun et al. [112]) could considerably reduce the burden of obtaining information about the individual's state and context.

When sensors are used to measure the tailoring variable, the person's value on the tailoring variables at a particular decision point would often be the output of a machine learning algorithm, such as support vector machine (SVM), which is used to process the raw data acquired through the sensors and classify the person's state and context. Kumar and colleagues [113] provide a comprehensive review of these procedures, illustrating the process by which heart beat patterns captured by ECG and sensor-based data on respiration patterns can be used to classify stress episodes [114], conversations [115], and smoking puffs [116]. Tapia and colleagues [117] provide a detailed discussion of how data captured by simple and ubiquitous sensors (e.g., door contact sensors on the fridge storing a timestamp each time the door is opened or closed) can be used to classify everyday activities in the home setting (e.g., eating).

Regardless of whether the assessment of a tailoring variable is active, passive, or both, careful consideration must be given to reliability and validity. Recall that the decision rules in a JITAI provide the link between the tailoring variable and the best intervention option. Valid and reliable tailoring variables are required in order for the decision rule to recommend the best intervention option. When one or more tailoring variables are measured unreliably, the decision rule will perform little better than randomly selecting an intervention option, and when one or more of the tailoring variables are invalid, the decision rule may even recommend a counterproductive intervention option (for more details see [31]).

Missing Data on Tailoring Variables

When designing a JITAI, scientists should anticipate and plan the functioning of the decision rule when measurements on the tailoring variables are missing. Missing data can occur for various technical reasons [118, 119], including data corruption (e.g., loss of data due to technical problems associated with how the data are stored); device detection failures (relevant in passive data collection where the sensing device fails because of technical limitations; e.g., absent mobile phone reception, battery failure); and human error (e.g., incorrectly using the device, failure to correctly self-monitor). Missing data can also occur due to poor engagement (e.g., individuals who are not engaged in a weight loss program are less likely to self-report food intake) and/or intervention fatigue (e.g., individuals not providing self-monitoring information because self-monitoring is too burdensome). In the last two cases, indicators of missingness may be used as tailoring variables that reflect poor engagement and/or intervention fatigue. In all cases, it is important to anticipate situations that may lead to missing data and ensure that the decision rules cover these situations.

Characteristics of Good Decision Rules in a JITAI

Good decision rules are based on an accurate and comprehensive scientific model that articulates experiences and contexts in which a person is likely to benefit from one intervention option vs. another in terms of the proximal outcomes. This scientific model should build on evidence concerning the dynamics of the health condition, as well as the dynamics of intervention adherence and retention. Specifically, it is important that researchers understand what constitutes a state of vulnerability and/or a state of opportunity, the temporal process by which these states emerge and relate to the distal outcome, and possible interventions that can be employed to address or capitalize on this process. An example involves understanding facilitators and barriers to adopting healthy eating habits, how and to what extent these facilitators/barriers might change over time, and the intervention options that can be employed just-in-time to capitalize on these understandings. Also important is the challenge of achieving adherence and retention to a just-in-time intervention. It is imperative to understand how and why intervention engagement and fatigue fluctuate over time, how these fluctuations impact the distal outcome(s), and what strategies can enhance engagement and reduce fatigue. Integrating evidence about both aspects of the clinical challenge—how to positively shape the dynamics of the health condition and how to redress dynamic barriers to intervention adherence/retention—lies at the heart of formulating good decision rules in a JITAI.

Challenges and Directions for Future Research

A major gap that hinders the development of efficacious JITAIs lies in the static nature of existing behavioral and intervention theories [10] and the lack of temporal specificity of theories that are more dynamic in nature. As discussed earlier, the development of an efficacious JITAI can be guided by a scientific model that integrates evidence concerning (a) the dynamics of the health condition and (b) adherence and retention in just-in-time interventions. However, most existing empirical/theoretical perspectives are not dynamic—they treat the mechanisms underlying health conditions and intervention adherence/retention as relatively stable, allowing them to vary, at most, as a function of baseline variables, such as personal characteristics (e.g., age, gender) and baseline symptom severity [9]. Even when existing theories or perspectives acknowledge the dynamic nature of underlying health condition and behavior change mechanisms, they often do not articulate how and to what extent these mechanisms might change over time and what kind of support should be offered to address them in a timely manner.

For example, consider emotional distress, a potential marker of an emerging state of vulnerability [37]. Although existing theories acknowledge that emotional distress is a dynamic construct that changes over time and hence needs to be regularly monitored and addressed, current theories and models do not specify its temporal dynamics (e.g., what constitutes meaningful changes in distress, how rapidly such changes are likely to occur [120, 121]). Moreover, although various types of evidence-based interventions exist to prevent or ameliorate distress, their translation and effective implementation in a just-in-time format would benefit from being informed by dynamic theories of intervention adherence/retention to guide the type, timing, and amount of support provision. Achieving such theoretical integration can be challenging, given that dynamic and comprehensive models of the mechanisms underlying intervention adherence/retention are rare and incomplete.

Of course, the lack of temporal specificity of current theories is only part of the story. Despite their limitations, current health behavior theories play a central role in the creation of behavior change and maintenance strategies [122], and applying them to build JITAIs has the potential to result in better outcomes compared to JITAIs that are not theoretically grounded [34, 123, 124]. However, many JITAIs lack the appropriate theoretical basis, perhaps due to the limited exposure of mobile application developers to health behavior theories [9]. While there are various theoretical overviews [125] and examples [126] that can guide JITAI developers, more attention should be given to developing cross-disciplinary collaborations to facilitate the appropriate use of theory in building JITAIs.

To facilitate the integration of current health behavior theories in JITAI construction, as well as the development of new theories and scientific models, a number of approaches have been proposed to organize existing evidence and identify open scientific questions [127]. These approaches require clear explication not only of the relationship between factors influencing the dynamics of the health condition (e.g., whether distress influences smoking), but also of how this relationship manifests and evolves at different timescales. A timescale is defined here as the size of the temporal interval within which a process, pattern, phenomenon, or event occurs (e.g., a day, a week) [50]. Specifically, timescale considerations require that JITAI developers think through the key mechanisms underlying the health condition, as well as the key mechanisms underlying intervention adherence/retention, and seek to articulate how they unfold over time towards the distal outcome. This can be facilitated by specifying key factors and effects within and between various timescales. These frameworks can be used not only to organize existing evidence in a way that is useful for JITAI development, but also to identify directions for further research that can build the foundation for more dynamic health behavior theories.

Building the empirical basis to construct such dynamic models requires study designs and analytic methods that capitalize on the rich, fine-grained, temporal data that can now be collected with ubiquitous mobile and wireless technology. For example, data analysis methods from engineering and statistics [122, 128, 129] can inform the construction of dynamic behavioral models. Smith and Walls [130] provide an extensive review of study designs and data analytic methods that can be used with data from mobile health studies to inform the development of scientific models for JITAI construction.

Study designs and data analytic methods to understand the causal effects of intervention options are needed as well. For example, recently Murphy and colleagues [131] introduced the micro-randomized trial (MRT) design—a form of a sequential factorial design that involves random assignment of intervention options at numerous decision points. This trial design allows investigators to address scientific questions concerning the causal effect on proximal outcomes of providing an intervention option compared to the alternative and whether this effect varies depending on an individual's internal state and context.

Other data analytic methods emerging in computer science are designed to continually re-adapt; that is, update the JITAI decision rules to an individual over time as s/he experiences the intervention. For example, MyBehavior [132] is a lifestyle mobile intervention that uses a "multi-armed bandit" data analysis method to modify decision rules as user behavior changes in the course of the intervention. MyBehavior uses sensor data to suggest a frequent behavior (e.g., walking) when the person is in a particular location and life context (e.g., on the way home after work). However, it also occasionally prompts infrequent higher-energy-expending behaviors that the person does only rarely (e.g., running) to allow the data analytic methods to learn whether the person would repeat these behaviors. If the person repeats these behaviors, the decision rule is modified so that the new, higher-energy expending behavior is recommended (instead of walking) when the person is in a particular context (e.g., after work hours).

Experimental and data analytic methods are evolving rapidly, offering increasingly exciting opportunities to improve the effectiveness of JITAIs and the utility of the scientific models that inform the design of these interventions. However, as noted by Kaplan and Stone [133], "most psychologists were trained to use statistical inference techniques designed for the study of agronomy in the 1930s." Accordingly, greater attention should be given not only to the development of new methodologies but also to training the next generation of researchers in study designs and analytic methods that are suitable for mobile health data.

Finally, a JITAI is defined in this manuscript as an intervention design in which decisions concerning when and how to provide support are intervention-determined rather than participant-determined. While this definition excludes interventions that rely solely on the individual's initiative to access and select from available supportive resources, adding some participant-determined features to a JITAI might have advantages. These include the ability to accommodate conditions in which the target individual is in the best position to know what kind of support is needed and when, facilitate autonomous regulation by giving the individual control over the supportive process, and introduce minimal waste and disruption (assuming individuals do not initiate support when they are unreceptive) [134]. Additional research is needed to investigate how to best add participant-determined features to a JITAI, so as to balance the provision of planned, externally initiated support with personal volition and agency [134].

Conclusion

This article articulates the scientific motivation and key components of interventions that use mobile devices to offer support in a timely, adaptive, and ecologically attuned manner. As we enter a new era that presents the technological capacity to individualize and deliver just-in-time interventions, there is critical need for sophisticated, nuanced psychological and health behavior theories capable of guiding the construction of such interventions. Providing timely and ecologically sound support for intervention adherence and retention holds the potential to counteract the law of attrition from technology-supported interventions.

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Compliance with ethical standards

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