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Just-in-Time Adaptive Interventions: Where Are We Now and What Is Next?

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Abstract

The past decade has seen a surge in developing just-in-time adaptive interventions (JITAIs)—an intervention approach that leverages advancements in digital technologies to address the rapidly changing needs of individuals in daily life. This article provides an overview of the state of science on JITAI development and highlights important directions for future research. We explain what a JITAI is (and what it is not) and review the scientific and practical rationales underlying this approach. We also call attention to three key challenges relating to the development of JITAIs. The first challenge is that individuals may not be able to engage with (i.e., invest energy in) an intervention when they need it most in daily life. The second concerns the generally suboptimal engagement of individuals in interventions that leverage digital technologies as currently implemented. The third concerns the paucity of research on ways to harness the power of social relationships in JITAIs. We conclude that much research effort is needed to build more sophisticated and effective JITAIs.

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INTRODUCTION

In the current era of rapid technological evolution, digital advancements shape societal activities in unprecedented ways. Mobile devices and wearable sensors are increasingly pervasive and support essentially every aspect of human activity. At the same time, there is a global crisis in health (Ngo 2023), and mental health concerns such as stress, anxiety, and depression are on the rise (Senger 2023). Digital technologies can be harnessed to address this crisis and support public health goals (Kickbusch et al. 2021). The widespread adoption of digital technologies offers tremendous opportunities for delivering psychological interventions in a way that is accessible and affordable. Advances in mobile and wireless technologies have the capacity to collect rich and granular data about people's states and contexts and leverage this information to deliver psychological interventions in (near) real time, in everyday life. Just-in-time adaptive interventions (JITAIs) can realize these opportunities by guiding how to use rapidly changing information about the person's state and context to decide whether and how to deliver psychological interventions in the moment (Nahum-Shani et al. 2018b).

Recent years have shown a tremendous rise in the development of JITAIs, including interventions to increase physical activity and reduce sedentary behavior (e.g., Hardeman et al. 2019), reduce substance use (e.g., Coughlin et al. 2024, Perski et al. 2022), support recovery from alcoholism (e.g., Gustafson et al. 2014), prevent suicide (e.g., West et al. 2022), decrease depressive symptoms (e.g., Everitt et al. 2021), manage daily stress (e.g., Schenkel et al. 2022), support smoking cessation (e.g., Battalio et al. 2021, Nahum-Shani et al. 2021a), and promote flow experiences at work (Bartholomeyczik et al. 2024). The goal of this article is to discuss the state of science on JITAI development as well as to highlight important directions for future research. We begin by explaining what a JITAI is (and what it is not) and reviewing the key components that comprise a JITAI. We then explain why JITAIs are needed, reviewing the scientific and practical rationales underlying this approach. We continue by discussing how empirically based JITAIs can be developed, including the importance of articulating a conceptual model to summarize existing evidence and using randomized experiments to answer open scientific questions about the best way to construct a JITAI. We then discuss three key challenges relating to the development of JITAIs to support health behavior change, and we highlight opportunities for future research to address each of these challenges. **Table 1** provides a glossary of key terms and concepts.

Table 1 Definitions of key terms

Term	Definition
Adaptation	The protocolized and evidence-based use of dynamic information about the individual to decide whether and how to intervene.
Just-in-time adaptive intervention (JITAI)	Intervention design in which rapidly changing information about the individual's internal state and context is used to decide whether and how to intervene in real time, in the individual's natural environment. Operationalized with if-then decision rules. In JITAIs, intervention options are adapted on a relatively fast timescale (e.g., every few hours, every day). JITAIs use the same decision rules for all individuals, at all times.
Micro-randomized trial (MRT)	Experimental design providing an empirical basis for developing a JITAI. Involves sequential randomizations on a fast timescale: Each individual is randomized to different JITAI options many times in the course of the experiment, and the length of the time interval between randomizations is relatively short (e.g., a few hours).
Standard adaptive intervention	Intervention design in which intervention options are adapted on a relatively slow timescale (e.g., every few weeks or months). A JITAI can be a component in a standard adaptive intervention.
Sequential, multiple assignment, randomized trial (SMART)	Experimental design providing empirical basis for optimizing a standard adaptive intervention. Involves sequential randomizations on a slow timescale: Each individual may be randomized among adaptive intervention options more than once, typically 2–3 times, and the length of the time interval between randomizations is relatively long (e.g., a few weeks or months).
Personalizing JITAI (pJITAI)	Intervention delivery framework in which artificial intelligence or methods from control systems engineering are used to update JITAI decision rules repeatedly, as individuals interact with the intervention over time, to continually optimize benefits. The term "personalizing" describes an attempt to further improve the capacity of JITAIs to address the changing needs of the person by adding another layer of adaptation on top of the adaptation process governing standard JITAIs.
Engagement	Investment of physical, cognitive, and affective energy in a given stimulus or task.
State of receptivity	Conditions in which an individual is likely to effectively engage with a specific intervention option.
State of opportunity	Conditions in which delivering an intervention is expected to promote a desirable proximal outcome.
State of vulnerability	Conditions that represent risk for an adverse proximal outcome.

JITAIs: WHAT, WHY, AND HOW?

What Is a JITAI?

A JITAI is an intervention design that guides the rapid adaptation of interventions. An intervention is defined as "a set of actions with a coherent objective to bring about change or produce identifiable outcomes" (Rychetnik et al. 2002, p. 119). The term "intervention design" refers to the approach (i.e., the procedures or guidelines) used to deliver an intervention in practice. JITAIs provide a guide for how interventions should be adapted in practice, where adaptation refers to the protocolized and evidence-based use of dynamic information about the individual to decide whether and how to intervene. Here, "dynamic" means information that can change over the course of the intervention, reflecting the person's state (e.g., feelings, behaviors) and/or context (e.g., location, presence of other people). While relatively stable information, such as demographics (e.g., age, race/ethnicity), predispositions (e.g., personality traits and attitudes) and preintervention conditions (e.g., symptom severity, prior treatment) may also be used in a JITAI

to decide whether and how to intervene, this use is complementary rather than integral to the definition of JITAI.

As an example, consider a JITAI for promoting oral self-care in underserved adults (loosely based on Nahum-Shani et al. 2024b), which we will use throughout for illustrative purposes. In this example, labeled JITAI-A throughout, information from sensors within an electric toothbrush is leveraged to decide whether to send a prompt from the mobile app (e.g., via a push notification) that contains a message encouraging the person to brush their teeth. Twice-daily, in the morning and in the evening, an hour before the person's prespecified brushing window, if data from the electric toothbrush indicate that the person did not brush their teeth in the past 12 hours, a prompt is delivered; otherwise, a prompt is not delivered.

As with any intervention designed for practice, the adaptation process in a JITAI is protocolized, meaning that there is a prespecified detailed plan for how dynamic information about the individual should be used in practice to make intervention decisions. This protocolization is intended to enhance intervention fidelity (i.e., the degree to which interventions are delivered as intended by their developers; James et al. 2017). Note that the adaptation process in JITAIs is very different from a process called intervention adaptation (Chambers & Norton 2016), which involves modifying an existing intervention program to create a new one (Salloum et al. 2022). For example, adapting a parenting intervention that was originally developed in Australia to the needs of Latino populations in Panamá involved adding an icebreaker activity at the start of the session—a common practice in this culture to facilitate social interaction—as well as changing the metaphors used to introduce parenting skills so that they would be more culturally relevant and reflect local challenges (Mejia et al. 2017). Thus, with intervention adaptation, an existing intervention is altered to improve its alignment with a new context, to target a new population, to make it more feasible to deliver, or to make it more acceptable to the population of interest (Salloum et al. 2022). In such a setting, adaptation refers to making decisions about whether and how to modify the intervention protocol, whereas in JITAIs it refers to making decisions about whether and how to deliver an intervention as part of a prespecified intervention protocol (Moore et al. 2013, Stirman et al. 2013). Further, "adaptation" in intervention adaptation refers to a scientific activity performed by an intervention scientist to improve an existing intervention, whereas in JITAIs "adaptation" refers to an intervention activity performed by the entity that delivers the intervention in practice (e.g., a mobile device).

The adaptation in JITAIs can be protocolized via decision rules—i.e., if-then statements that clearly specify the conditions in which different interventions should be delivered. The decision rule in the sidebar titled Example 1 protocolizes the JITAI-A described above. The decision rules include three elements: (*a*) intervention options: different types of interventions, tactics, intensities, or delivery modalities; (*b*) tailoring variable(s): information used to decide which intervention option to deliver; and (*c*) thresholds/levels of the tailoring variable(s) (or some weighted linear or nonlinear combination of tailoring variables) that differentiate between the conditions in which different intervention options should be delivered. The decision rules provide a clear protocol for the adaptation by linking the tailoring variables to the intervention options, thus articulating which intervention option should be delivered under different conditions. In JITAIs the adaptation happens rapidly, namely on a relatively fast timescale—every few days, hours, minutes, or seconds. The adaptation is initiated at decision points, which are points in time in which intervention decisions should be made. To adapt intervention delivery rapidly, JITAIs include rapid decision points, meaning that there are many (e.g., hundreds or thousands) decision points over the course of the intervention, with a relatively short time interval (e.g., a few hours or a few minutes) between them.

A JITAI can be a stand-alone component in an intervention program, but in many cases it is combined with other intervention components, such as an onboarding session (Nahum-Shani et al. 2024b); pharmacotherapy (Nahum-Shani et al. 2021a); counseling, coaching, or health education sessions (Robbins et al. 2022, Spring et al. 2024, Yang et al. 2023); on-demand content that can be accessed at any time via the mobile device (Carey et al. 2024); incentives (Kramer et al. 2019); and various types of contact (e.g., messaging, emails, phone calls) intended to increase intervention adherence (Hardeman et al. 2019). Further, an intervention program can include more than one JITAI. For example, an intervention to improve the health and well-being of care partners of older adults [inspired by Carlozzi et al. (2021)] may combine two JITAIs: One JITAI uses data about the care partner's physical activity (collected via a wrist sensor) by midday to decide whether to send them a physical activity suggestion, and another JITAI uses daily diary data about the care partner's (self-reported) mood to decide each evening whether to deliver a brief strategy for regulating negative mood.

Similarly, a weight management intervention for obese and overweight adults [inspired by Pfammatter et al. (2019)] may combine two JITAIs: One JITAI uses information from a weight loss app about the person's self-monitoring behaviors to decide, three times daily—following the person's prespecified mealtime—whether to remind them to self-monitor their dietary intake. The other JITAI uses information from the app about whether the person has achieved their current daily calorie goal by the end of each day to decide whether to deliver a message encouraging them to plan their meals for the next day. Regardless of whether a specific JITAI is employed as a standalone component or in combination with other components, it should be not only protocolized but also evidence-based, that is, grounded in clinical/practical expertise, best available research evidence, and the perspectives and experiences of key people of interest, such as those the intervention is intended to support (Briner & Rousseau 2011, French 2002). Efforts to gather the evidence necessary for developing JITAIs should be guided by the scientific and practical motivation for this intervention approach, which is discussed in the next section.

Why Are JITAIs Needed?

There are two key motivations for JITAIs. The first concerns improving the overall effectiveness of an intervention program, namely the extent that the intervention "does more good than harm" (Flay 1986, p. 451). The second motivation concerns improving the resource efficiency of an intervention program, namely the extent that the intervention can do more good with fewer resources (van Ewijk 2018).

Intervention effectiveness. The decision rules in a JITAI are intended to impact proximal outcomes (i.e., short-term mechanisms of change) to achieve a desirable distal outcome (i.e., a long-term clinically meaningful goal). To impact proximal outcomes, JITAI decision rules are designed to (*a*) address states of vulnerability and/or opportunity in relation to the proximal outcomes, and (*b*) deliver a specific intervention option only when the individual is receptive to that option.

A state of vulnerability reflects conditions that represent risk for an adverse proximal outcome. For example, for smokers attempting to quit, stress represents a state of vulnerability for a smoking lapse (an isolated smoking episode) in the following hours (Battalio et al. 2021). For individuals with bulimia nervosa, experiencing craving during the day represents a state of vulnerability for binge eating in the evening (Leenaerts et al. 2024). For individuals in recovery from alcohol dependence, proximity to their favorite bar or liquor store represents a state of vulnerability for a relapse (Gustafson et al. 2014).

A state of opportunity reflects conditions under which delivering an intervention is expected to promote a desirable proximal outcome. For example, the time immediately after the completion of a self-monitoring task via a mobile app represents an opportunity to deliver a reward to reinforce subsequent self-monitoring (Nahum-Shani et al. 2021b). Experiencing negative work events (e.g., problems getting along with a coworker, unclear task assignments) represents an opportunity to enhance employee awareness of negative work-related emotions (e.g., hostility, frustration) and learn adaptive strategies for regulating them (Zhu et al. 2024). Self-reporting restrictive eating represents an opportunity for individuals with eating disorders to practice cognitive behavioral therapy skills in daily life between treatment sessions (Juarascio et al. 2023).

Certain states may represent both vulnerability for an adverse outcome and opportunity for positive change (Nahum-Shani 2024). For example, a JITAI to support patients with kidney stones in their efforts to develop a habit for regular fluid intake (Conroy et al. 2020, 2024) delivers a reminder to drink if the patient did not exceed a prespecified threshold for fluid intake in the previous 60 min. The assumption is that not meeting this prespecified threshold represents a state of vulnerability for not achieving fluid consumption sufficient to produce greater than 2.0–2.5 L of urine daily, the standard clinical guideline for preventing a recurrence of stones. However, this state— not exceeding a prespecified threshold for fluid intake in the past 60 min— is also conceptualized as an opportunity for habit formation. Specifically, the assumption is that delivering a reminder in this state has the potential to promote habitual fluid consumption (Conroy et al. 2020). A behavior (e.g., fluid consumption) becomes habitual when a stable contextual stimulus (e.g., the passage of time since the last drink) comes to trigger an automatic impulse to perform the behavior. This context–behavior association is established through repetition. If the person did not perform the behavior despite the contextual stimulus (e.g., they did not meet the fluid intake threshold in the past 60 min), sending a reminder can increase the likelihood of the behavior. With ongoing repetition, the context becomes sufficient to activate the association, such that the context (the passage of time since the last drink) will trigger an impulse to perform the behavior (drinking) with minimal cognitive effort or need for reminders (Harvey et al. 2021, Moors & De Houwer 2006).

By delivering the right type of intervention, at the right time, to address states of vulnerability and/or to capitalize on states of opportunity for positive change, the overall effectiveness of the intervention (i.e., the distal outcome) is expected to increase. However, effectiveness can be undermined if the person is not receptive to the type of intervention delivered. Receptivity reflects the conditions in which an individual is likely to effectively engage with a specific intervention option. This implies that receptivity is intervention specific (Nahum-Shani et al. 2023)—under specific conditions a person may be receptive to one intervention option but not to another.

The concept of engagement is key to defining receptivity. Engagement captures the extent that an individual invests physical, cognitive, and emotional energies in a focal stimulus or task (Nahum-Shani et al. 2022c); engagement is considered effective if these energies are invested in a way that does more good than harm (Nahum-Shani & Yoon 2024). Thus, to operationalize receptivity, it is important to clearly identify the stimuli and tasks comprising the specific intervention option. For example, consider an intervention option in the form of a prompt from a mobile device encouraging the person to be aware of their work-related emotions and to take a short walk to regulate them. This intervention option includes a stimulus (the message from the mobile device) and two main tasks (paying attention to one's emotions and taking a short walk). This means that receptivity to this intervention option reflects the conditions in which the person is likely to effectively engage with the message (e.g., when they are not driving) as well as with emotional awareness (e.g., when they are not preoccupied with another demanding task) and walking (e.g., when they are not in a meeting). By delivering a specific intervention option when the

individual is receptive to that option, effective engagement with the intervention option is expected to increase, thus promoting the overall effectiveness of the intervention.

In summary, the first key motivation for JITAIs is to deliver the most effective intervention option given the individual's current state in daily life. This means delivering an intervention option that can address a given state of vulnerability for an adverse outcome, and/or capitalize on a window of opportunity for positive change, only when the individual is best able to engage with this specific intervention option. JITAIs are designed for settings in which there is no intervention option that is always effective for everyone.

Intervention resource efficiency. The decision rules in JITAIs are designed to avoid unnecessary intervention delivery by specifying the conditions in which specific intervention options should not be delivered (e.g., when the person is not experiencing states of vulnerability and/or opportunity, or when they are not receptive to these intervention options). Avoiding unnecessary intervention delivery is expected to reduce the overall effort participants are asked to invest in the intervention and thus minimize burden, mental fatigue, and habituation. Here burden is defined as "the perceived amount of effort that is required to participate in the intervention"(Sekhon et al. 2017); mental fatigue is defined as "a psychobiological state caused by prolonged periods of demanding cognitive activity and characterized by subjective feelings of tiredness and lack of energy" (Jacquet et al. 2021, p. 76); and habituation is defined as diminishing response resulting from repeated stimulation that is not attributed to fatigue or adaptation (Moskowitz & Sussman 2023, Reyes-Jiménez et al. 2020). Minimizing burden, mental fatigue, and habituation can also improve intervention engagement, thereby promoting the overall effectiveness of the intervention. Thus, resource efficiency has the potential to promote intervention effectiveness.

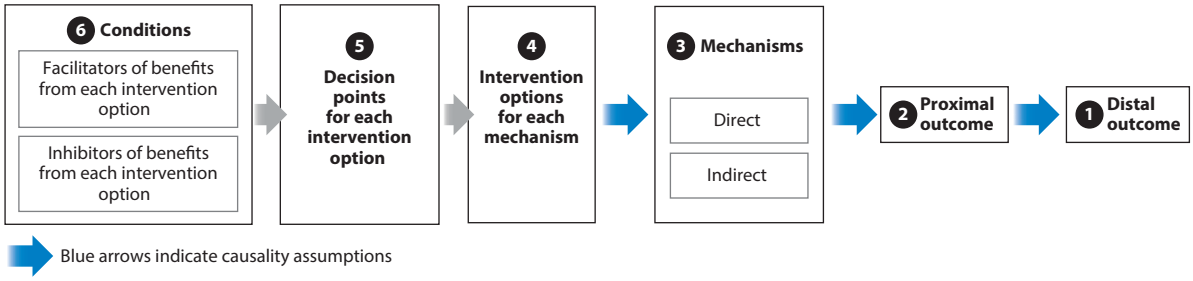
In summary, the second key motivation for JITAIs is to do more good with fewer resources. Specifically, the goal is to minimize the extent that individuals invest unnecessary effort in the intervention, thus reducing burden, mental fatigue, and habituation.

How to Empirically Develop Effective and Resource-Efficient JITAIs?

An important first step in the process of developing an effective and resource-efficient JITAI is to articulate a conceptual model based on existing empirical and practical evidence. This model can be used to identify gaps in evidence and to articulate open scientific questions that motivate research studies.

A conceptual model to guide JITAI development. A conceptual model to guide the development of JITAIs should describe (*a*) the primary distal outcome, (*b*) the primary proximal outcome, (*c*) the most influential mechanisms of change that likely impact the proximal outcome, (*d*) the intervention options that may impact these mechanisms, (*e*) the decision points relevant to each intervention option, and (*f*) the conditions that are expected to facilitate or inhibit benefits from each intervention option. **Figure 1** provides a summary of this process.

Selecting outcomes. The first step in articulating a conceptual model is to select the primary distal outcome that motivates the intervention. This outcome should reflect a clinically meaningful change that can be achieved over a prespecified time frame and should be informed by the target population and the problem to be addressed. Suppose that the primary outcome motivating a JITAI for promoting oral self-care in underserved adults is to achieve 50% adherence to brushing recommendations (twice-daily, for 2 minutes each) over 10 weeks. The distal outcome should guide the selection of the proximal outcome, which reflects a mechanism that unfolds over a relatively short timescale. A mechanism is defined here as a causal pathway (e.g., processes or events) through which change is expected to occur in a specific outcome, in this case the distal outcome.



* The numerical ordering indicates suggested steps to guide the process, although the process is likely iterative

Figure 1

Guidelines for articulating a conceptual model to inform the development of a JITAI.

There are often several contender proximal outcomes, in which case investigators may select those that (*a*) are expected to have the greatest impact on the distal outcome and (*b*) can be changed in a meaningful way by delivering an intervention (Nahum-Shani et al. 2015). For simplicity, the discussion below (as well as **Figure 1**) focuses on a single proximal outcome, but it can also be used to guide investigators in a setting where multiple proximal outcomes are of interest. Suppose that proximal brushing behavior (i.e., over a period of 12 hours) was selected as the primary proximal outcome. The next step is to specify mechanisms that likely impact this proximal outcome.

Specifying mechanisms that impact the proximal outcome. The mechanisms that impact the selected proximal outcome may be direct and/or indirect. Direct mechanisms are pathways that are expected to directly impact the proximal outcome. For example, forgetfulness may directly impact proximal brushing behaviors. Indirect mechanisms are pathways that are expected to indirectly impact the proximal outcome through (i.e., by directly impacting) another mechanism. For example, improving participants' understanding of the relationship between their oral health and general health (Botelho et al. 2022, Watt & Aida 2022) may directly improve the participant's motivation and thus indirectly promote proximal brushing behaviors.

Selecting intervention options. After identifying the most influential mechanisms that impact the proximal outcome, investigators should consider whether and how each mechanism can be impacted by intervention delivery. This includes selecting specific intervention options that are expected to impact each mechanism. For example, forgetfulness can be impacted by delivering a reminder in the form of a motivational message; engagement with brushing feedback in the app can be impacted by delivering a prompt to encourage the person to view the feedback.

Identifying decision points. The decision points at which each intervention option may be delivered should be specified based on scientific and practical considerations. Scientific considerations include the nature of the intervention option under consideration and the rationale behind it. For example, reminders intended to improve twice-daily brushing behaviors (in the morning and evening) should be considered before the person's typical morning and evening brushing windows. In contrast, feedback to promote self-reflection on brushing behaviors may be insightful when summarized over a few days; thus, a prompt encouraging the person to access the feedback may be beneficial if delivered on a slower timescale (e.g., every few days). Note that a decision point does not necessarily mean that an intervention will be delivered (e.g., a prompt will be sent); rather, it means that a decision will be made (here, by the mobile device) about whether to deliver a specific intervention option. It is possible that a decision point will result in no intervention delivery (e.g., no prompt; see the sidebar titled Example 1).

EXAMPLE 1: A JUST-IN-TIME ADAPTIVE INTERVENTION FOR PROMOTING ORAL SELF-CARE IN UNDERSERVED ADULTS

Twice-daily (morning and evening), 1 hour prior to the person's pre-specified brushing time:

If brushing in the past 12 hours = No
Then intervention = [Deliver a prompt to encourage brushing]
Else intervention = [No prompt]

Specifying facilitating and inhibiting conditions. Specifying the conditions under which delivering each intervention option is expected to facilitate or inhibit benefits in the intended mechanism is critical for ensuring that each intervention option is (*a*) delivered when it is likely to be effective and (*b*) not delivered when it is unnecessary or potentially harmful. To formulate these conditions, investigators should consider both states that reflect vulnerability/opportunity in terms of the target mechanisms and states that reflect receptivity to the specific intervention option under consideration. For example, if the person did not brush in the past 12 hours, they might be at risk for subsequent failure to brush in the next 12 hours. Thus, sending a reminder may be most beneficial if the participant did not brush in the past 12 hours; otherwise, delivering a reminder may be unnecessary. Further, if the participant received two reminders on the previous day, they may not be receptive to another reminder (e.g., due to burden or fatigue); in this case, delivering a reminder may be more harmful than beneficial.

Articulating a scientific model to inform the development of JITAIs requires empirical and practical evidence, but the evidence available to an intervention developer is often insufficient. Different experimental designs can be leveraged to build this evidence depending on the scientific questions of interest.

Experimental designs to inform JITAI development. An experimental design is an approach used to systematically manipulate independent variables to answer causal questions. While observational studies may also be used to answer causal questions, they require untestable structural assumptions compared to experimental designs (Kaufman 2019). Below, we review several experimental designs and the types of questions about JITAIs these designs can be used to answer. We begin with the micro-randomized trial (MRT) design, which can be used to answer scientific questions about how best to construct a specific JITAI. We then discuss other experimental approaches that can be used to answer questions about the performance of a specific JITAI and to determine how best to integrate it with other digital or nondigital components.

Micro-randomized trials. These designs can be used to answer scientific questions about the selection of intervention options in a JITAI and the conditions that facilitate and inhibit their intended benefits. An MRT is an experimental design that involves sequential randomizations on a fast timescale (Qian et al. 2022) to match the fast timescale of adaptation that characterizes the JITAIs these designs are intended to inform. Sequential randomizations imply that the same person may be randomly assigned to intervention options more than once in the course of the trial, and when the sequential randomizations happen on a fast timescale, it means that the same individual may be randomly assigned to intervention options many times in the course of the trial, with a relatively short time interval (e.g., a few days, hours, or minutes) between each randomization. For example, suppose that investigators have the following questions about the construction of a JITAI for promoting oral self-care in underserved adults: (*a*) Is it beneficial for promoting brushing behaviors in the next 12 hours to deliver (versus not deliver) a motivational prompt an hour before the

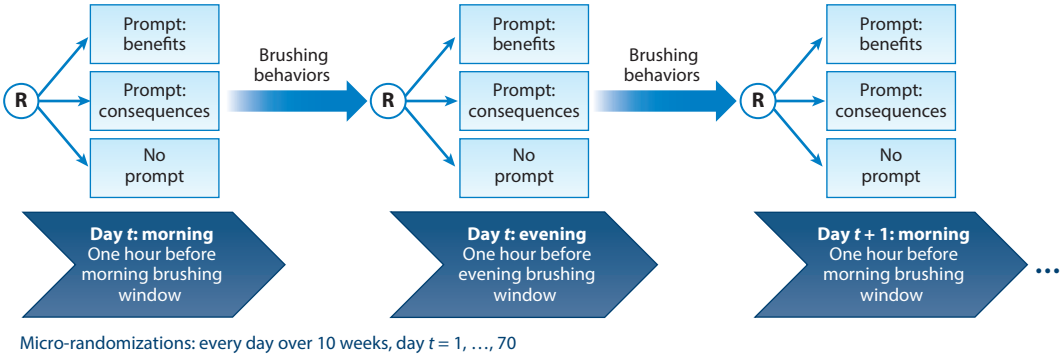


Figure 2

Hypothetical micro-randomized trial.

person's prespecified brushing window? (*b*) What type of motivational prompt is most beneficial in promoting brushing behaviors, a prompt that focuses on the benefits of brushing or a prompt that focuses on the consequences of not brushing? And (*c*) is the prompt more beneficial for promoting brushing behaviors in the next 12 hours if sensors from the electric toothbrush detect no brushing (versus any brushing) in the past 12 hours? To answer these questions, an MRT (see **Figure 2**) can be used to randomly assign participants twice-daily, in the morning and in the evening, or an hour before the person's prespecified brushing window to three intervention options: (*a*) a motivational prompt that focuses on the benefits of brushing; (*b*) a motivational prompt that focuses on the consequences of not brushing, or (*c*) no prompt. Throughout the 10-week MRT, sensors within the electric toothbrush can continuously assess brushing behaviors, and these data can be used to address the three abovementioned questions (for examples of how similar questions can be addressed, readers may consult Bidargaddi et al. 2018, Carpenter et al. 2023, and Nahum-Shani et al. 2021b). The existing literature provides guidelines for designing MRTs (Qian et al. 2022, Walton et al. 2018), planning sample size for MRTs (Cohn et al. 2023, Liao et al. 2016), and analyzing data from MRTs to answer questions about the selection and adaptation of intervention options in a JITAI (Boruvka et al. 2018, Qian et al. 2022). Since these designs allow investigators to leverage within-person and between-person contrasts to estimate effects, they are highly efficient in terms of sample size requirements (Collins et al. 2024, Nahum-Shani et al. 2022b).

While the MRT is suitable for answering scientific questions about the selection and adaptation of intervention options within a JITAI, investigators often have questions about the performance of a specific JITAI and how best to integrate it with other digital or nondigital components. The trial designs described below can be useful in answering these questions.

Two-arm or multi-arm randomized trials. These designs are useful for answering three main types of questions about a JITAI: (*a*) Is a digital intervention with a given JITAI better than the standard of care? (*b*) Is a given JITAI better than another JITAI? And (*c*) is it beneficial to combine (versus not combine) a given JITAI with another intervention component? To answer these questions, participants may be randomly assigned to two or more experimental conditions at a single time point—typically at program entry. For example, consider the oral self-care JITAI described above (i.e., JITAI-A) and suppose that investigators would like to answer the following question: Is a digital intervention that includes this JITAI more beneficial in increasing brushing behaviors in the next 10 weeks compared to the standard of care (i.e., oral self-care educational materials)? In this case, participants can be randomly assigned to two experimental conditions at program entry (see **Figure 3**): either the JITAI or the standard of care. Alternatively, suppose that

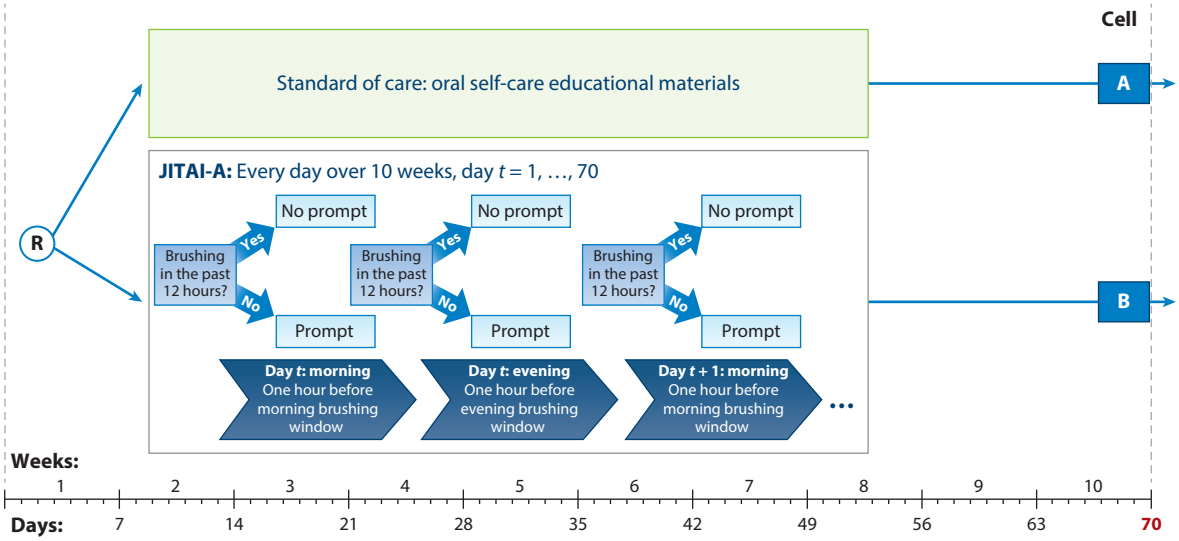


Figure 3

Hypothetical two-arm trial comparing JITAI-A to the standard of care.

investigators would like to answer the following question: Is JITAI-A, which delivers motivational messages based on prior brushing behaviors, more beneficial in increasing brushing behaviors in the next 10 weeks relative to a more costly JITAI, referred to as JITAI-B, which delivers small monetary rewards based on prior brushing behaviors? In this case, participants can be randomly assigned to either JITAI-A or JITAI-B at program entry. Finally, consider the following question: Is it beneficial in terms of increasing brushing behaviors in the next 10 weeks to combine (versus not combine) JITAI-A with a remote coaching session? In this case, participants can be randomly assigned to either JITAI-A alone or JITAI-A combined with a coaching session at program entry. Investigators may consider randomly assigning participants to more than two arms (i.e., experimental conditions) if their questions concern the comparison of more than two options (e.g., comparing a JITAI to two types of control conditions or comparing three types of JITAIs). These trials typically require a larger sample size to the extent that the number of arms increases.

Factorial designs. These designs are useful for answering scientific questions about the benefits of combining a given JITAI with multiple other components at program entry and about how well these components work together. Factorial designs are randomized trials that involve more than one factor, where a factor is defined here as an independent variable that is manipulated as part of the experiment. In factorial designs, the levels of each factor are crossed with the levels of the other factors to form a design with multiple experimental conditions. In standard factorial designs, randomizations to experimental conditions occur at a single time point, typically at program entry. For example, suppose that investigators have the following questions about the benefits, in terms of increasing brushing behaviors over the next 10 weeks, of combining JITAI-A with three other components at program entry: (*a*) Is it beneficial to combine (versus not combine) JITAI-A with a remote coaching session? (*b*) Is it beneficial to combine (versus not combine) JITAI-A with contingent financial rewards (e.g., a small monetary incentive delivered if the participant brushed for 7 consecutive days)? And (*c*) is it beneficial to combine (versus not combine) JITAI-A with emails that address nonadherence (e.g., a health coach delivering an email if the participant did not brush for 7 consecutive days)?

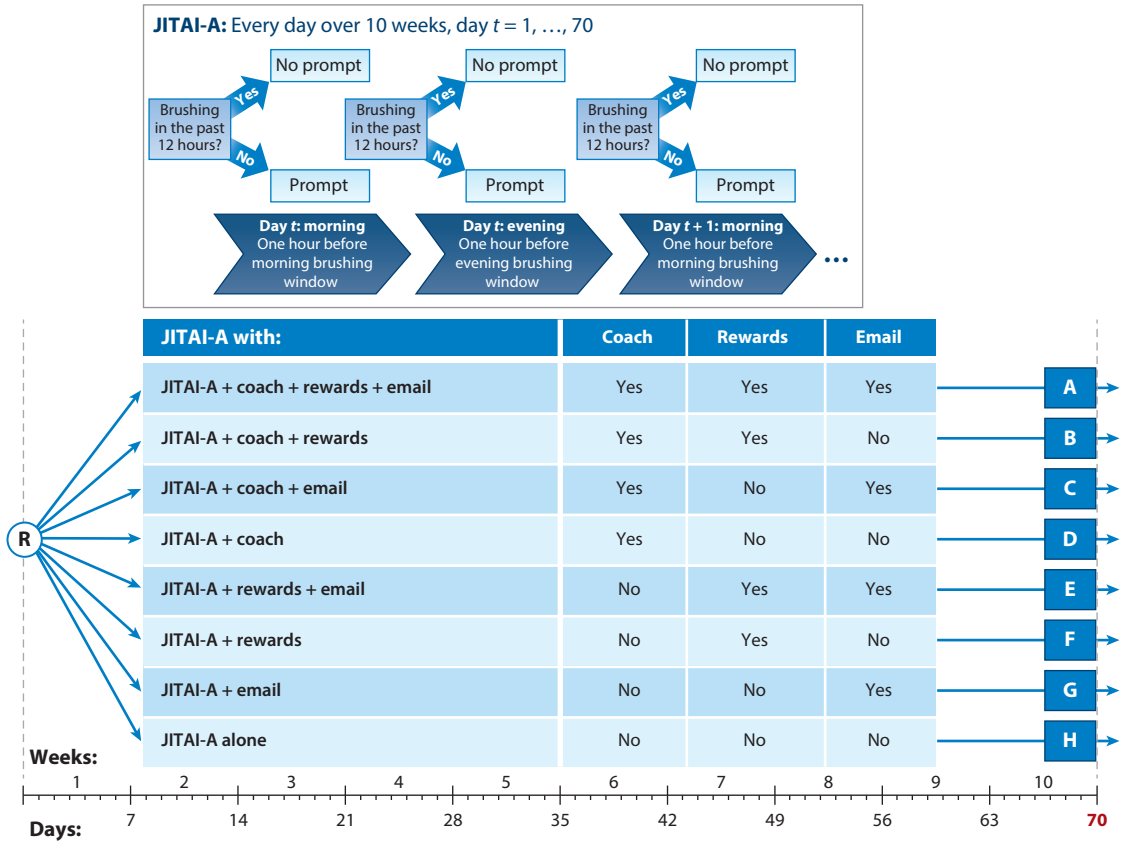


Figure 4

Hypothetical factorial design to investigate combining JITAI-A with multiple other components at program entry.

To answer these questions the investigators can consider a factorial design (see **Figure 4**) whereby JITAI-A is offered to all participants at program entry and three factors are manipulated: (*a*) adding coaching, (*b*) adding contingent financial rewards, and (*c*) adding emails to address nonadherence. Each factor will have two levels (yes or no), and participants will be randomly assigned to eight experimental conditions resulting from crossing the two levels of each of the three factors (i.e., a $2 \times 2 \times 2 = 8$ factorial design). The existing literature (e.g., Collins 2018; Collins et al. 2009, 2024; Dziak et al. 2012; Nahum-Shani et al. 2018a) demonstrates the efficiency of these designs for testing the main effects and interactions between factors, thereby answering scientific questions about the benefits of combining the JITAI with each component and about how well these components work together (e.g., does adding coaching work well with adding emails?)

The sequential multiple assignment randomized trial. This design can be used to answer scientific questions about how best to combine a given JITAI with other intervention components that are adapted on a relatively slow timescale (i.e., every few weeks or months). Here, a given JITAI is one intervention component within a standard adaptive intervention (Collins et al. 2004, Nahum-Shani et al. 2012). An adaptive intervention is an intervention design that guides the adaptation of interventions on a slow timescale, with the goal of addressing conditions that change relatively slowly. Thus, in standard adaptive interventions, compared to JITAIs, there are only a few decision

points, and the length of the time interval between them is relatively long (e.g., a few weeks or a few months). Indeed, a JITAI might be an intervention option in a standard adaptive intervention (Carpenter et al. 2023, Spring et al. 2024). For example, an adaptive intervention for promoting oral self-care in underserved adults may begin with offering JITAI-A as a first-line intervention option; participants who 5 weeks later fail to consistently adhere to the recommended brushing behaviors (i.e., who do not brush on average at least once per day) may be classified as early nonresponders and moved to the second-line intervention, which involves augmenting JITAI-A with weekly remote coaching sessions for the next 5 weeks, whereas those who adhere to the recommended brushing behaviors are classified as early responders and continue with JITAI-A for the next 5 weeks. Here, the decision of whether to add weekly coaching to the first-line intervention option (i.e., to JITAI-A), happens on a slow timescale, 5 weeks after program initiation. The sequential, multiple assignment, randomized trial (SMART) (Lavori & Dawson 2000, Murphy 2005) is a randomized trial that involves sequential randomizations on a slow timescale to match the timescale of the adaptation in the standard adaptive interventions it is intended to inform. For example, suppose that investigators have the following questions: (*a*) At program entry, which first-line intervention option is more beneficial in promoting brushing behaviors in the next 10 weeks, JITAI-A alone or JITAI-A combined with a remote coaching session? And (*b*) at week 5, which second-line intervention is more beneficial in promoting brushing behaviors in the next 10 weeks for individuals who show early signs of nonresponse, adding weekly coaching sessions or adding contingent financial rewards (i.e., delivering a small monetary incentive if the participant brushed for 7 consecutive days)? These questions concern two decision points (i.e., at program entry and at week 5); thus, answering these questions requires a trial design that involves sequential randomizations at each of these decision points. Specifically, investigators may consider a SMART (see **Figure 5**) whereby individuals are first randomized to either JITAI-A alone or JITAI-A combined with a brief coaching session. Then, at week 5 individuals who show early signs of nonresponse (i.e., who fail to consistently adhere to the recommended brushing behaviors) are rerandomized to augment the first-line intervention either with weekly coaching sessions or with contingent financial rewards; those who show early signs of response (i.e., who consistently adhere to the recommended brushing behaviors) continue with the same first-line intervention option (i.e., they are not rerandomized). The existing literature demonstrates the efficiency of SMARTs for answering scientific questions about the selection and adaptation of intervention options at two or more decision points in a standard adaptive intervention (Collins et al. 2014, Seewald et al. 2020, Yap et al. 2023).

Summary. Whether the goal is to construct a JITAI, integrate it with other components, or evaluate it relative to a suitable control, an important step in selecting an experimental design is to clearly articulate the scientific questions of interest based on the conceptual model guiding the investigation. While recent growth in experimental designs and data analytic approaches for developing JITAIs enables investigators to answer a wide variety of scientific questions, several challenges require further research to fully realize the potential that JITAIs hold for promoting behavior change.

CHALLENGES AND OPPORTUNITIES IN DEVELOPING JITAIs

In this section, we review three key challenges relating to the development of JITAIs to support health behavior change. The first challenge is that individuals may not be receptive to digital interventions when they experience the states of vulnerability/opportunity that the JITAI is intended to address. The second concerns the generally suboptimal engagement of individuals in digital interventions as currently implemented. The third challenge concerns the paucity of research on

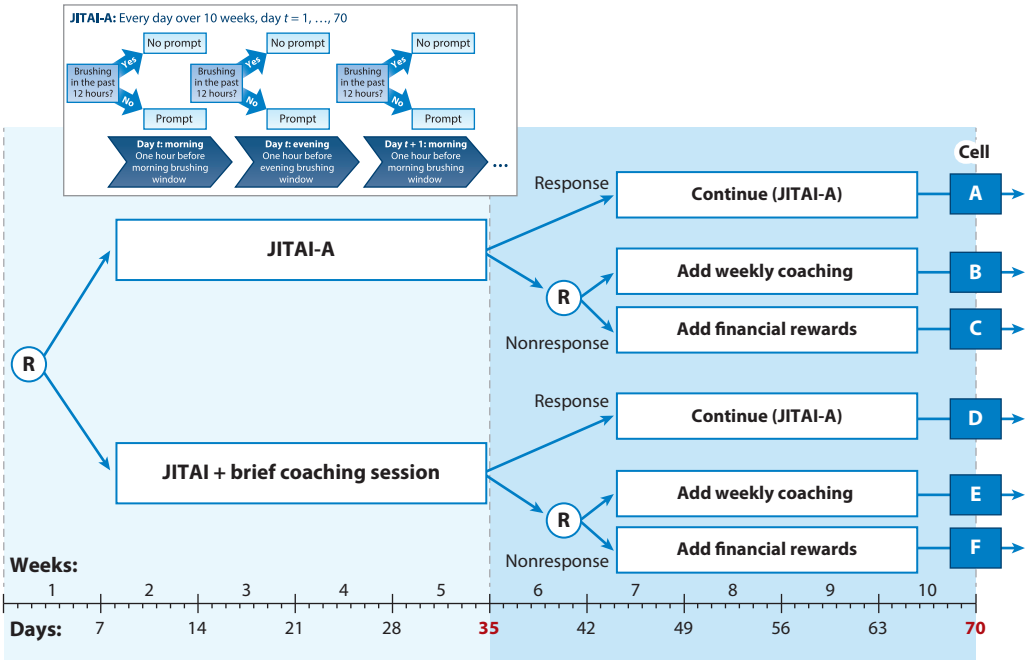


Figure 5

Hypothetical sequential, multiple assignment, randomized trial (SMART) to investigate combining JITAI-A with other intervention components that are adapted on a relatively slow timescale.

ways to leverage social relationships in JITAIs. We discuss opportunities for future research to address each of these challenges.

Unreceptivity to Digital Interventions During States of Vulnerability and/or Opportunity

As explained earlier, receptivity is a key concept in designing effective JITAI, as it reflects the conditions in which an individual is likely to effectively engage with a specific intervention option. Thus, JITAIs are motivated to deliver an intervention option only when the individual is in a state that combines near-term vulnerability for an adverse outcome, and/or near-term opportunity for positive change, with receptivity to the specific intervention option under consideration. Individuals may not be receptive to a specific intervention option for various personal and/or contextual reasons (e.g., because they are driving, preoccupied with urgent matters, or in the presence of other people). Some of these reasons may be directly connected to the state of vulnerability/opportunity. For example, negative work events—a state of opportunity for a prompt that recommends learning adaptive strategies for regulating work-related emotions—can happen in work-related situations (e.g., when the person is in a meeting) that limit the person's ability to use a mobile device or engage with tasks that are not work-related. In the hour before a person's prespecified morning brushing time—a state of opportunity for delivering a mobile-based prompt to encourage brushing—the person may be in a hurry to get ready for work and may not be able to notice the digital prompt. Stress—a state of vulnerability for a lapse in smokers attempting to quit—may lead to cognitive impairments (Lupien et al. 2007) that limit the person's ability to attend to a mobile-based prompt and process the content delivered. These settings pose challenges to the design of JITAIs because

individuals may rarely be receptive to a digital intervention when they need it most (i.e., in states of vulnerability and/or opportunity).

An important step in addressing these challenges is to conduct research to systematically investigate the extent that individuals are receptive to a specific intervention option when they are vulnerable and/or when they experience a window of opportunity for positive change. MRTs can be leveraged to randomly assign individuals to different intervention options (e.g., different prompts with different recommendations) sometimes when they are vulnerable (e.g., when they experience stress) and sometimes when they are not vulnerable (e.g., when they don't experience stress) and to assess their engagement with the intervention options following each randomization. The data can be used to investigate whether individuals are more likely to engage with (i.e., are more receptive to) specific types of intervention options when they are in states of vulnerability/opportunity versus when they are not in these states.

If research indicates that individuals are not receptive to specific intervention options during states of vulnerability/opportunity, then investigators may consider approaches to modifying these options, such as simplifying their content or design. Likewise, investigators may develop alternative intervention options that target more indirect mechanisms of change, such as skill building, where a skill is defined as the ability to carry out a specific task in a particular context, developed through experience or training (Buffardi et al. 2000, Du et al. 2022, Fischer et al. 1990). For example, investigators may consider designing JITAIs that deliver microtraining— that is, intervention options designed to engage individuals in tasks that can improve their ability to prevent and better manage future states of vulnerability and/or to facilitate and leverage future states of opportunity for positive change (Bernstein et al. 2019); these tasks are designed to be brief and easily fitted into daily routines (e.g., positive self-talk, mindful attention, planning, mental imagery). Future research would benefit from investigating how best to construct JITAIs that deliver microtraining, including identifying the conditions in which individuals may be receptive to different intervention options that employ this approach.

A key related challenge in leveraging MRTs to investigate receptivity to intervention options in a JITAI is the need for valid measures of momentary engagement. First, while digital tools offer many opportunities to measure physical engagement with certain stimuli and tasks (e.g., physical engagement with a mobile-based prompt can be measured with app usage data, and physical engagement with brushing can be measured with sensed data from an electronic toothbrush), engagement with nondigital tasks (e.g., stress-management strategies such as deep breathing and mindful attention) is more challenging to measure. Measuring engagement with such tasks often requires asking the person to self-report their experiences, thus adding intervention burden. Second, the investment of physical energy (e.g., clicking on the prompt) is only one dimension of engagement; the investment of cognitive energies (e.g., reading and processing the message) and the investment of emotional energies (e.g., appreciating the content) are less straightforward to assess on a momentary basis without the added burden of self-report. Third, as explained earlier, a specific intervention option may include a collection of interconnected stimuli and tasks with which participants are expected to engage. For example, a prompt from the mobile device encouraging the person to use a stress-management activity (e.g., mood surfing) on the mobile app (Battalio et al. 2021) requires, first, engagement with the message, and then engagement with the series of digital (e.g., audiovisual) and nondigital (e.g., mental imagery) stimuli and tasks comprising the stress-management activity. This requires careful consideration of how to capture the multifaceted nature of intervention options in a JITAI when measuring participant engagement. Overall, research attention should be given to developing new measures of momentary engagement with intervention options in a JITAI to advance our knowledge of receptivity.

Engagement with Digital Interventions Is Suboptimal

Empirical evidence suggests that engagement with the current generation of digital interventions, including JITAIs, is generally suboptimal (see Nahum-Shani & Yoon 2024, Nahum-Shani et al. 2022c). Since participant engagement is critical for intervention effectiveness, this empirical evidence raises several opportunities for future research. First, collaborating with individuals and communities with lived experience when designing digital interventions offers tremendous potential for promoting engagement. Iterative design procedures can be leveraged to workshop ideas based on frameworks such as coproduction, codesign, participatory design, or user-centered design that guide the process of partnering with people of interest (e.g., individuals with lived experience, community members, care providers, policymakers) in order to build an intervention that is well aligned with their needs, capabilities, skills, and limitations (Grande et al. 2024).

Second, human-delivered support can be integrated with JITAIs to promote engagement. Human-delivered components (e.g., coaching, therapy sessions) have the potential to increase engagement with JITAIs by facilitating accountability (i.e., an expectation that one's actions or decisions will be evaluated by others and that the individual will need to justify these actions or decisions; O'Donoghue & Van Der Werff 2022, Wallace et al. 2011) and therapeutic alliance (i.e., a collaborative relationship between patient and therapist characterized by an emotional bond, agreement on treatment goals, and joint work on treatment tasks; Babl et al. 2024). Human-delivered components can typically be adapted on a much slower timescale relative to JITAIs. Moreover, human-delivered components are relatively costly, burdensome, and subject to structural supply barriers such as those caused by a shortage of care providers (Diel et al. 2024, Spring 2019). Thus, future research should focus on investigating how best to construct multimodality adaptive interventions (MADIs)—that is, intervention designs that blend JITAIs with human-delivered components that are adapted on a slower timescale (Nahum-Shani & Naar 2023). The hybrid experimental design (HED; Nahum-Shani et al. 2022a, 2024a) is a new experimental approach that can be used to answer scientific questions about how best to construct MADIs. These designs involve sequential randomizations on multiple timescales—slow and fast, corresponding to the timescales at which different components can be delivered and adapted over the course of a MADI. HEDs are highly efficient for answering questions about building MADIs, including questions about how well digital and human-delivered components work together, and they can take various forms depending on the components under consideration and the scientific questions motivating the trial (Collins et al. 2024; Nahum-Shani et al. 2022a, 2024a).

Third, engagement can be enhanced through continual improvement of the JITAI as participants experience and interact with the intervention. In standard JITAIs, while the specific decision (i.e., the selected intervention option) may not be the same from one decision point to the next, the decision rules are deterministic and fixed. A deterministic decision rule takes the individuals' state and context as an input (e.g., their brushing behaviors based on data from the electric toothbrush) and outputs a specific intervention option (e.g., delivering or not delivering a prompt from the mobile app). When the decision rule is fixed, it remains the same across all decision points over the course of the JITAI and across all individuals. For example, consider the decision rule governing JITAI-A (see the sidebar titled Example 1). This specific decision rule is employed at every given decision point (i.e., twice-daily, in the morning and evening) and for all individuals offered this intervention. Deterministic and fixed decision rules limit the capacity of JITAIs to accommodate unknown factors (e.g., extreme weather conditions, technological evolution, or simply habituation) that affect engagement with and response to the intervention options. Personalizing JITAIs (pJITAIs) is an intervention design that uses artificial intelligence (AI) or methods from control systems engineering to continually learn, based on participants' accruing data, when

participants are most likely to engage with and respond to the intervention options (Coughlin et al. 2024; Ghosh et al. 2024; Trella et al. 2022, 2024). While the term "personalization" has different meanings in different fields, it is used here to describe an attempt to further improve the capacity of JITAIs to address the changing needs of the person by adding another layer of adaptation on top of the adaptation process governing standard JITAIs. As explained earlier, JITAIs include decision rules that operationalize the adaptation of intervention options—namely, the use of dynamic information about the person to decide whether and how to intervene. In pJITAIs, these decision rules are themselves adapted over time based on information gathered over the course of the intervention about the person's responsivity to the decision rules. In other words, pJITAIs continually learn whether the decision rules are performing well and modify them as needed. To make this learning process possible, pJITAIs powered by AI algorithms use stochastic (rather than deterministic) decision rules, meaning that these decision rules take the participant's state and context as an input and output a specific probability of delivering an intervention option.

For example, consider the decision rule in the sidebar titled Example 2, which specifies that twice-daily (in the morning and evening), if data from the electric toothbrush indicate that the person did not brush their teeth in the past 12 hours, a prompt encouraging them to brush their teeth should be delivered with probability 0.7; otherwise, a prompt should be delivered with probability 0.4. This stochastic approach enables the pJITAI to learn whether candidate decision rules are performing well, because it generates variability in the delivery of intervention options under specific states and contexts. Suppose that the decision rule in the sidebar titled Example 1 was employed over the first intervention week (for a total of 14 decision points per person) across 100 individuals. In this case, 100% of the decision points in which individuals did not brush in the past 12 hours would result in a prompt, and 0% of these decision points would result in no prompt; in other words, employing this decision rule leads to no variation in prompt delivery. Now, suppose that the decision rule in the sidebar titled Example 2 was employed over the first intervention week across 100 individuals. In this case, on average 70% of the decision points in which individuals did not brush in the past 12 hours would result in a prompt, and 30% of these decision points would result in no prompt. This variation in prompt delivery provides data that the pJITAI can analyze at prespecified times during the intervention to compare delivering versus not delivering a prompt in terms of proximal engagement and/or response. Thus, a pJITAI may start with employing the stochastic decision rule shown in the sidebar titled Example 2 but every week analyze the data gathered so far to fine-tune the decision rule. Specifically, the data analyzed would include the intervention options delivered at prior decision points, the brushing behaviors before these decision points, and the proximal brushing behaviors following these decision points. The goal would be to assess whether delivering (versus not delivering) a prompt to participants who did not brush in the past 12 hours improves subsequent brushing behaviors. If there is sufficient evidence in favor of prompting, the pJITAI will increase the probability of delivering a prompt (e.g., from 0.7 to 0.8). If there is sufficient evidence in favor of not prompting, the pJITAI will decrease the probability of delivering a prompt (e.g., from 0.7 to 0.5). This approach has the potential to improve engagement by amplifying the capacity of the decision rules to address the changing needs of the person. Moreover, the stochastic decision rules may have an added value with respect to engagement, as the variability they generate in prompt delivery (e.g., occasionally, the participant may not receive a message if they failed to brush in the past 12 hours) can add novelty to the intervention and facilitate recovery (i.e., the renewal or restoration of energy expended in the course of the intervention; Kühnel et al. 2012).

EXAMPLE 2: A STOCHASTIC JUST-IN-TIME ADAPTIVE INTERVENTION FOR PROMOTING ORAL SELF-CARE IN UNDERSERVED ADULTS

Twice-daily (morning and evening), 1 hour prior to the person's pre-specified brushing time:

If brushing in the past 12 hours = No
Then intervention = [Deliver a prompt with probability 0.7]
Else, *if* brushing in the past 12 hours = Yes
Then intervention = [Deliver a prompt with probability 0.4]

Finally, engagement may also be enhanced by facilitating greater human agency, defined as "the capacity to exercise control over the nature and quality of one's life" (Bandura 2001, p. 1). Generative AI—techniques capable of creating seemingly new content (e.g., text, images, audio) from training data—can play an important role in allowing individuals to make intentional choices that shape the JITAI delivered to them. For example, JITAIs can provide opportunities for individuals to communicate, via text or audio, their needs and preferences regarding the content or timing of the prompt. Generative AI can be used to interpret this input, leading to personalized constraints on the type and timing of intervention delivery (Pang et al. 2023). JITAIs can also allow individuals to communicate personal challenges or concerns through written or spoken messages. In this case, generative AI could be used to interpret these messages and then recommend an existing intervention option related to that challenge or concern (Cao et al. 2024). Research is needed to investigate how best to leverage generative AI to promote engagement with JITAIs in a way that is effective, safe, and ethical.

Harnessing the Power of Social Relationships

Promoting health behavior change often requires interventions that leverage existing social relationships (e.g., with peers or care partners) to impact the target person. For example, parents likely influence their child's oral health behaviors (Arrow et al. 2013). To promote oral health in young children, it may be beneficial to design interventions that focus on the child, the parent, and their social relationships, so that the parent can effectively support and empower the child. However, social relationships are complex and dynamic. They can impact behavior change through different mechanistic pathways and over multiple timescales—fast and slow (Smyth et al. 2017). Current JITAIs are designed to deliver interventions to a single individual rather than to coordinate intervention delivery to two or more interdependent individuals. This brings unique opportunities for developing JITAIs that address the changing needs of two or more interconnected individuals at the appropriate timescales.

JITAIs that leverage social relationships to facilitate behavior change should be informed by a conceptual model that describes not only the direct and indirect mechanisms of change but also the interconnected mechanisms through which the social relationship and each constituent member can impact the proximal outcome. Here, interconnected mechanisms of change refer to causal pathways that are expected to indirectly impact the proximal outcome by directly impacting the social relationships.

Figure 6 provides a hypothetical conceptual model to guide a JITAI that seeks to leverage and facilitate positive parent–child social relationships to enhance the child's proximal brushing behaviors. Here, the child's level of forgetfulness may directly and adversely impact their daily brushing (the proximal outcome). However, parent oral health support may directly improve the child's oral health self-efficacy and facilitate a home environment in which oral health is valued,

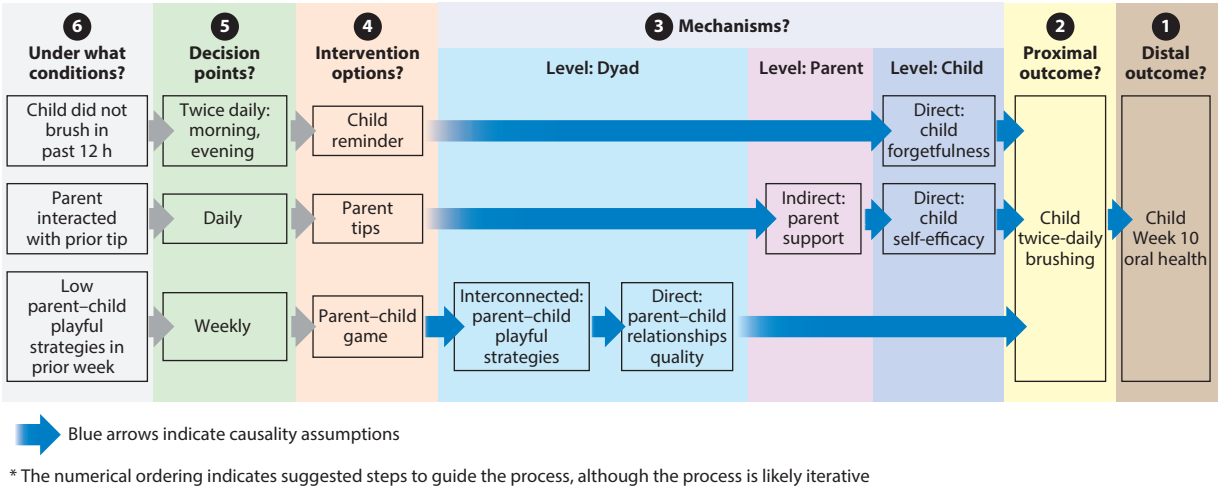


Figure 6

Example conceptual model to inform a JITAI that leverages dyadic social relationships.

and thus indirectly promote the child's daily brushing behaviors. Furthermore, parent–child playful strategies (e.g., games, songs, entertaining videos) related to oral health may directly promote positive parent–child relationships, thus indirectly promoting child's daily brushing. Different intervention options may impact each of these mechanisms, with intervention options that target interconnected mechanisms likely to be delivered at a higher level (e.g., the parent–child dyad) compared to those targeting other direct (e.g., the child) or indirect (e.g., the parent) mechanisms. For example, child forgetfulness can be addressed via a twice-daily reminder sent to the child before each brushing window; parent oral health support can be improved by sending daily messages to the parent with tips to support their child's oral health; and playful strategies can be promoted by sending both the child and the parent a new game they can play together each week while the child is brushing their teeth. The decision points for each intervention options will also likely vary depending on the mechanisms they target, with intervention options that target interconnected mechanisms likely requiring decision points on a slower timescale, as larger social units take longer to interact, coordinate, equilibrate, and converge in a shared experience (Casari & Tagliapietra 2018, Cronin & Bezrukova 2019, Goodstein et al. 1994). Similarly, the conditions that facilitate or hinder the benefits from each intervention option will likely be at the level of the unit targeted by the intervention option.

As with standard JITAIs, articulating a conceptual model for a dyadic JITAI requires empirical and practical knowledge, but existing data are often insufficient. Given the multilevel and multitimescale nature of JITAIs that leverage social relationships to promote behavior change, new experimental and data analytic approaches should be developed to enable researchers to address scientific questions about how best to construct these JITAIs.

CONCLUSION

Digital technologies offer tremendous potential for delivering timely interventions that address the rapidly changing needs of people in daily life. However, in order to take advantage of technologies to deliver JITAIs it is critical to understand their boundary conditions, namely, when this type of intervention can be useful versus when another intervention design should be considered. It is also critical to conduct research to inform the development of effective and resource-efficient

JITAIs. MRTs can be used to answer scientific questions about how best to construct a JITAI, while other experimental approaches can be used to answer scientific questions about the overall performance of a JITAI and about how best to integrate a JITAI with other intervention components. The choice of experimental design should depend on the scientific questions motivating the study. We recommend that investigators begin with articulating a conceptual model to guide intervention development, then identify open scientific questions based on this model, and finally select the trial design most appropriate for answering those questions.

Clarifying the conceptual model underlying JITAI development not only helps identify research questions but also enhances reproducibility in JITAI research. As with any scientific inquiry, reproducibility—the ability of independent researchers to obtain similar results using comparable methods and procedures (Goodman et al. 2016)—is essential for advancing the field. Digital technology enhances reproducibility by offering more consistent intervention delivery than human-delivered support. However, its rapid evolution introduces challenges, as the technologies used for JITAI delivery in one study may soon become obsolete, complicating replication efforts. Transparency regarding the conceptual model guiding JITAI research, along with comprehensive documentation of procedures, can help ensure that as technologies evolve, the underlying scientific knowledge and assumptions remain replicable and testable.

While existing methodologies provide a solid foundation for empirically informing JITAI development, we recommend advancing trial designs and methodologies to enable the creation of more sophisticated JITAIs. These should more effectively leverage AI-based methods for greater personalization and harness the power of social relationships to facilitate behavior change.

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The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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