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Modeling the decreasing intervention effect in digital health: a computational model to predict the response for a walking intervention

Master Thesis

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Abstract

In past digital health interventions, an issue has been that participants drop out over time which is referred to as the "law of attrition" (Eysenbach, 2005). Based on this, we propose that though initially, participants respond to the intervention, there is a hypothesized second diminishing effect of an intervention. However, we suggest that on top, there is a third effect. Independent of the individual notification or nudge, people could build the knowledge, skills and practice needed to independently engage in the behavior themselves (schraefel and Hekler, 2020).

Using behavioral theory and inspired by prior animal computational models of behavior, we propose a dynamical computational model to allow for a separation of intervention and internalization. It is targeted towards the specific case of the *HeartSteps* intervention that could not explain a diminishing immediate effect of the intervention, second hypothesized effect, while a person's overall steps remained constant, third effect (Klasnja et al., 2019). We incorporate a habituation mechanism from learning theory that can account for the immediate diminishing effect. At the same time, a reinforcement mechanism allows participants to internalize the message and engage in behavior independently. The simulation shows the importance of a participant's responsiveness to the intervention and a sufficient recovery period after each notification. To estimate the model, we use data from the HeartSteps intervention (Klasnja et al., 2019; Liao et al., 2020), a just-in-time adaptive intervention that sent two to five walking suggestions per day. We run a Bayesian estimation with Stan in R.

Additional validation tests are needed to estimate the accuracy of the model for different individuals. It could however serve as a template for future just-in-time adaptive interventions due to its generic structure. In addition, this model is of high practical relevance as its derived dynamics can be used to improve future walking suggestions and ultimately optimize notification-based digital health interventions.

Keywords: computational modelling, dynamical systems, just-in-time intervention, digital health, physical activity

1 Introduction

Participants of digital health studies have been shown to drop out over time, which has been referred to as the "law of attrition" (Eysenbach, 2005, p. 1). The law of attrition poses a problem in various fields across digital health: In social media interventions, there frequently was a dropout rate of 20% according to a meta-analysis by Williams et al. (2014). Even more, in computer-based trials to improve depression, a meta-analysis found that 57% of people did not complete the studies (Richards and Richardson, 2012). In studies targeting drinking, attrition rates up to 42% were found (Riper et al., 2011). Similarly, physical activity (PA) interventions report attrition rates between 25 and 40% (Spittaels et al., 2007; Anderson-Bill et al., 2011; Kelders et al., 2011). All these interventions have usually tried to avoid attrition and keep participants active throughout the study.

At the same time, researchers in digital health also strive to support their participants to build the knowledge, skills and practice to engage in healthy behavior independently (schraefel and Hekler, 2020). There have been efforts to empower participants in digital health interventions such that they engage in new behaviors themselves (Samoocha et al., 2010; Sousa et al., 2020). However, these usually do not focus on participants' behavior outside of the intervention and evaluate the effect size on whether participants reacted to the intervention (Samoocha et al., 2010; Sousa et al., 2020). Hence, we suggest to incorporate a slower process into experimental designs that allows for a positive overall outcome of the intervention even if participants drop out. Participants are supported as long as they need it, but they are eventually empowered to engage in healthy behavior independently of the immediate effect of the intervention.

Such an intervention type would show three effects. First, there presumably is an effect of the intervention, immediately after nudges or notifications are sent. Second, with repeated exposures to the intervention, the effect decreases, leading many people to drop out after some time (Eysenbach, 2005). Third, throughout the trial, people will internalize the message of the intervention such that they engage in the behavior independently and improve their behavior overall. With this, we explicitly separate the decreasing effect, the key hypothesized driver of attrition, from the internalization of knowledge, skills and practices.

We recognized a pattern of independent immediate (second hypothesized effect) and overall behavior (third effect) in an intervention that sends context cues to walk. This *HeartSteps* intervention was evaluated via a micro-randomized trial design, which enables disaggregation of these two effects (Klasnja et al., 2019).

Participants were randomized to receive walking suggestions or not as notifications up to five times per day for a period of 40 days. For all 37 participants, a PA wearable (Jawbone Up) measured their steps per minute and their phones tracked their location. Based on a person's calendar and if they snoozed notifications, it was determined if a person was available and if available, were randomized to receive a notification or not. Though participants responded well and walked 66% more steps after a notification initially, the response diminished over time (Klasnja et al., 2019). Yet, in the overall trajectory of daily steps across the 40 days, the participants did not show this decline (Klasnja et al., 2019). Klasnja et al. (2019) could not explain this effect. Such a diminishing response to the intervention (second hypothesized effect) is similar to the law of attrition (Eysenbach, 2005). Both describe decreasing responses to the intervention. However, the law of attrition corresponds to a nomothetic phenomenon, a certain percent of users drop out (Eysenbach, 2005). It does not necessarily describe that idiosyncratically, users can also exhibit a decreasing response to subsequent deliveries of notifications as a mechanism that could partially explain the nomothetic observation of attrition. We define the idiosyncratically decreasing immediate reaction after repeated responses like in *HeartSteps* as the *decreasing intervention effect*. The effect as we define it relates to the *immediate* reaction and leaves room for a potentially independent *longterm* process that drives internalization (third hypothesized effect).

Specifying the computational dynamical model

To explore the decreasing intervention effect and the potential for internalizing the skills, knowledge and practice, we build a dynamical computational model that allows for a separation of intervention and internalization. The computational model was informed by the *HeartSteps* intervention, but with the aspiration of the model to be informative for other interventions as well. Computational models are a key method to model dynamics as traditional statistical models are not suited to model its complexity (Hekler et al., 2016; Spruijt-Metz et al., 2015). Mathematical descriptions of dynamical phenomena can explicitly state how a model's compartments are related and how they interact over time (Smaldino, 2017). The dynamical hypothesis is then iteratively formalized within a simulation environment (Chevance et al., 2020). First, the simulation itself is essential to understand and analyze the hypothesis. It should match the current knowledge of behavior change, e.g. such that at the end of the day, participants stop walking when they are tired (Choi et al., 2019). Second and more importantly, the simulation gives the researcher the opportunity to study the inherent model dynamics and draw conclusions from it. Hence, computational models are well-suited to articulate and analyze a new set of dynamics such as a potential separation of intervention and internalization.

The central focus of this dynamical model therefore is to specify the dynamics that translate into the separation of the rapid intervention effects and internalization, particularly a decreasing short-term reaction to the notification and a constant long-term walking response.

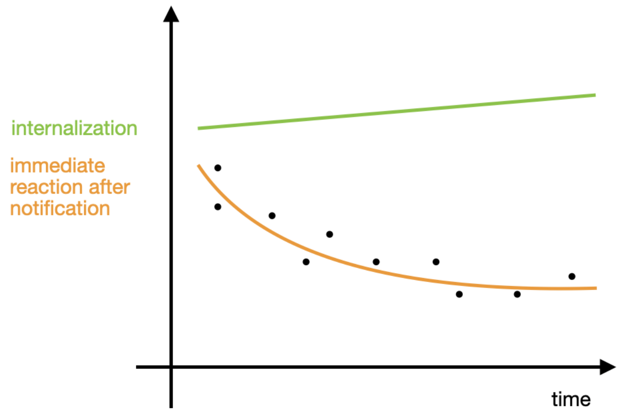


Figure 1: The decreasing intervention effect with an overall increase in walks.

In order to account for both a decreasing short-term and a constant long-term walking behavior, there needs to be a dynamic that differentiates between the effect of the notification and the long-term dynamic that drives the overall walking. Behavioral learning theory provides a good starting foundation. It splits up processes into stimulus (S), response (R) and consequence (C) (Skinner, 1953). This way, the effect of the input notification (S) is separate from the the consequence (C) reinforcing the response walking (R) that could drive the overall response (Skinner, 1953). We therefore base this model in the SRC framework and use it to allow a separation of the intervention and internalization.

We argue that to achieve the highest effect of the trial, the correct timing and a person's situatedness becomes essential (Nahum-Shani et al., 2018; Choi et al., 2019). The intervention delivery needs to be tailored to a person's state such that a person potentially maximizes how much is internalized from it. One way of tailoring has been proposed in just-in-time adaptive interventions (JITAIs), which 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" (Nahum-Shani et al., 2018, p. 448). The *HeartSteps* intervention is such a JITAI, which is why this model explores the specific case of JITAIs. To tailor notification delivery, it is theorized that there are four stages of receptivity for an intervention, perception, availability, adherence and performance (Choi et al., 2019). The dynamical model proposed here integrates two of these stages to optimize notification delivery. It includes factors that resemble availability as well as a process to mirror adherence.

This paper therefore has two goals:

1. Our aspiration is to deliver a framework to explain the decreasing intervention effect, while also accounting for internalization. It should potentially allow people to build the knowledge, skills and practice people need to engage in healthy behavior independently of the intervention.

2. For the specific context of the *HeartSteps* intervention, we aim to optimize future JITAIs, derive insights to the dynamics of such intervention and ultimately improve the timing of future walking interventions.

2 The model in the Stimulus-Response-Consequence framework

The model has six decisive features, and each will be elaborated in this section:

1. **the decreasing intervention effect** - part 1 of the separation of intervention and internalization, modeled by the S in the SRC framework
2. **internalization of the intervention** - part 2 of the separation of intervention and internalization, modeled by the C in the SRC framework
3. **processing variables** - to account for human behavior in the physiological SRC framework
4. **availability** - to account for internal and external barriers
5. **adherence** - to account for the decision to walk, based on decision theory
6. **different time aggregations** - to account for historical data that influence the decision

2.1 Separation of intervention and internalization: The decreasing intervention effect

In the SRC framework, the behavioral response (R) to a repeated stimulus (S) decreases and is called habituation (Groves and Thompson, 1970; Rankin et al., 2009). In the same manner, the decreasing intervention effect could be represented by the repeated notification (S) and could therefore follow similar dynamics to habituation. Past studies have found that participants indeed can get accustomed to repeated notifications (S), they ignore them and even habituate to them (Anderson et al., 2016; Vance et al., 2019). Habituation as described by Staddon (2001) follows a negative exponential distribution in the response. The model includes Staddon's 1-unit stimulus type habituation model with a two-parameter integrator N_t for the perception of the stimulus, visualized in figure 2. The γs used here and all following γs are idiosyncratic gain parameters. Mathematically, it follows the following dynamic:

$$\begin{aligned} N_0 &= 0 \\ N_t &= \gamma_{11} S_{t-1} + \gamma_{12} N_{t-1} \\ impS_t &= S_{t-1}(1 - N_{t-1}) \end{aligned} \tag{1}$$

The integrator N_t drives the decreasing impact of the stimulus. It is the gradually increasing "inhibitory effect" (Staddon, 2001, p. 118), see figure 2. The resulting impact of the stimulus $impS_t$ is then the stimulus subtracted by the growing inhibitory effect, hence being responsible for the eventual idiosyncratic downward short-term response.

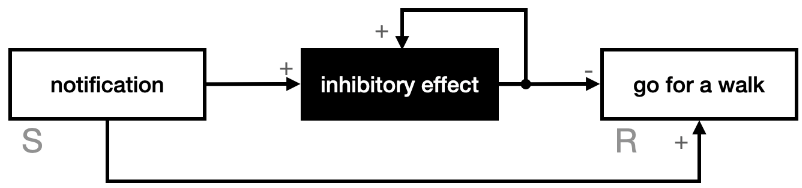


Figure 2: Modelling the decreasing intervention effect as a 1-unit stimulus-type habituation model with a two parameter integrator as the inhibitory effect N_t as proposed by Staddon (2001) within the stimulus-response framework.

2.2 Separation of intervention and internalization: The internalization

The second part of the separation of intervention and internalization requires the long-term walking behavior to be independent from the decreasing short-term response to the notification. In the SRC framework, separate from whether a stimulus was given or not, a satisfactory consequence (C) of an action (R) drives participants to repeat this action (Skinner, 1953), which is also considered the law of effect (Thorndike, 1898). If we perceive the consequence (C) of walking (R) to be mostly positive, we assume that walking induces future episodes, the more a participant walked, the more likely they are to walk in the future because of a positive consequence (C). Behavioral models call this mechanism "reinforcement" (Skinner, 1953, p. 65). This reinforcement is not influenced by the notification directly and could work independently of it. Internalizing the intervention is therefore modeled by positive reinforcement from walking, see figure 3.

We incorporate reinforcement both as a fast- and slow-changing process. The fast-changing process immediately feeds back into the system, the slow-changing process builds up over longer periods of time (Lunansky et al., 2020), see section 2.6. In the frame of building knowledge, skills and practice, both slow and fast reinforcement from walking matches the notion of building practice (schraefel and Hekler, 2020). Just like practice is established with more reinforcement, skills and knowledge could be modelled by a regularly reinforced compartment as well as other accumulative mechanisms (e.g. self-regularization, memory). We only model the process of internalizing practice, but recognize that it could be expanded to model other internalization processes as well.

To assess the degree of the slower process of internalization, this computational model relies on a continuous timeline. In JITAIs, the focus is mostly on the moment after a notification has been sent. Models often do not employ a continuous timeline but only highlight the time steps after the notification that are relevant to the proximal outcome of the intervention (Nahum-Shani et al., 2018; Klasnja et al., 2019). Hence, to describe the an overall behavior not just after notifications, the behavior would have to be monitored throughout the intervention, not just after a notification. Thus, we utilize a continuous timeline in the dynamical computational model.

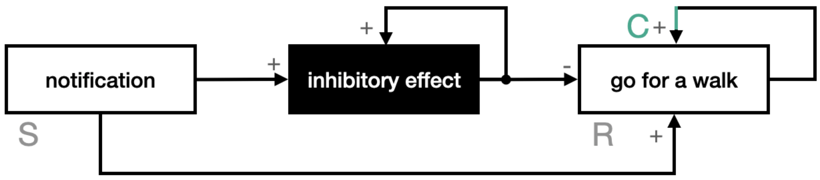


Figure 3: Modelling the overall increase of walks by introducing reinforcement from walking, the consequence (C) in the stimulus-response-consequence framework.

2.3 Modelling processing variables

The SRC framework represents physiological processes of learning. In physiology, there is a direct link of the stimulus (S) to the response (R) (Skinner, 1953). The reasons, mediators and moderators of engaging in physical activity however are manifold and more diverse than such an S-R link (Rhodes et al., 2019; Aromatario et al., 2019; Carey et al., 2018; Dishman et al., 1985). An example from self-determination theory for this is motivation. There, motivation takes an important role in mediating the notification to physical activity. Motivation is itself driven by factors like individual differences, the type of goal, the environment or the psychological needs of the person like autonomy (Fortier et al., 2007; Rhodes et al., 2019; Deci and Ryan, 2000). In digital health interventions, one cannot assume a direct notification (S) - physical activity link. The model will therefore need to be extended to target human behavior.

Hence, we add an intermediate compartment between the stimulus (S) and walking. Out of all possible factors, we choose a generic term for simplicity and describe the processing step as attitude A_t, a general term that can include both implicit and explicit evaluations as well as affective and instrumental attitudes

(Gawronski and Bodenhausen, 2014). The notion of attitude also fits into the learning framework: of all psychological constructs, attitudes are foremost viewed to be the result of learning (Doob, 1947). This is why reinforcement from walking proposed in section 2.2 can now be assigned to flow back into the attitude towards walking, see figure 4. By introducing the attitude A_t, the model can better represent human behavior in the learning framework SRC.

2.4 Modelling availability

To tailor the notification to the needs of a person, we consider two of the four receptivity stages in JITAIs proposed by Choi et al., availability and adherence (2019). *Availability* is defined as "when a user is capable of engaging in a target behavior suggested by the JIT intervention, and it is acceptable based on personal and social norms, disregarding motivational factors" (Choi et al., 2019, p. 5). Factors that influence availability can be sitting in a class or meeting, working, social settings, eating, physical conditions, being in a vehicle, talking on the phone, activity type and being focused on the current task among others (Sarker et al., 2014; Choi et al., 2019). In line with the introduction of a continuous timeline for this model, we extend the concept of availability from a state of opportunity for the JITAI to work (Nahum-Shani et al., 2018) towards a state of opportunity for the participant to engage in the behavior. This shifts the focus of availability, adherence and performance from a state when it is best to receive a notification to a state when it is best to engage in the internalized behavior. The contextual variables I_t and E_t resemble these internal and external barriers that prevent participants from walking because a participant is unavailable.

The basic model now contains the SRC loop from learning theory extended by availability variables and a processing step to match human behavior. Similar to attitude, the availability compartments are kept generic in the model diagram to be able to represent a number of variables. Its generic structure consists of only three compartments: notification, attitude and walking, see figure 4.

2.5 Modelling the decision to walk

As soon as a participant is available, he or she can potentially advance to the next step of receptivity, *adherence*, and "perform a target behavior" (Choi et al., 2019, p. 5). Adherence is a binary assessment of whether or not a person engaged in that behavior or not. Though the *HeartSteps* intervention considers availability

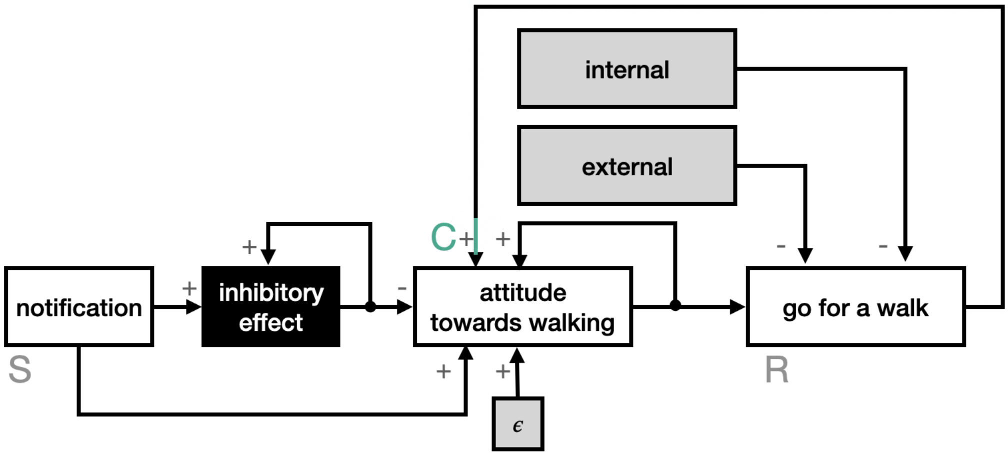


Figure 4: The model is an extended SRC learning loop: the notification S_t, the intermediate step coined as attitude A_t, and walking W_t including two exogenous availability variables. The walking reinforcement to attitude A_t is the consequence (C).

variables, it does not explicitly account for adherence variables when deciding to send a notification (Klasnja et al., 2019).

Models in computational digital health often employ linear relationships (Martin et al., 2020; Freigoun et al., 2017; Conroy et al., 2019). In such a setting, if a person is not available, he or she would walk *less*, but would rarely stop walking completely. Be it a meeting, sleep or just long sedentary intervals, at each instance t, a person would be walking. This formalization of walking as continuous was possible based on past treatment of t as one day. Consequently, for more frequent sampling of t, a different definition of walking is needed. To allow a person to have time intervals without walking, there needs to be a threshold between walking and not walking. For simplicity, and in line with the binary concept of adherence, we introduce only two categories and set walking to be binary.

Instead of having a deterministic threshold, we postulate that a set of factors influences the *probability* of a person walking and eventually the person taking a *decision* to go for a walk or not go for a walk. According to Gold and Shadlen (2007), such a decision is theorized to be a process in the brain that reallocates probabilities dependent on a set of factors, shown by figure 5. Within this decision framework, we define the variable W_t as a walking bout.

We set the overall likelihood to walk to be *Bernoulli*-distributed. It returns a binary decision for walking. Accordingly, walking W_t is a stochastic sequence of independent Bernoulli random variables $W_t \in \{0, 1\}$ with a time-dependent probability $Pr\{W_t = 1\} = p(U_t)$, where $W_t = 1$ represents the participant is

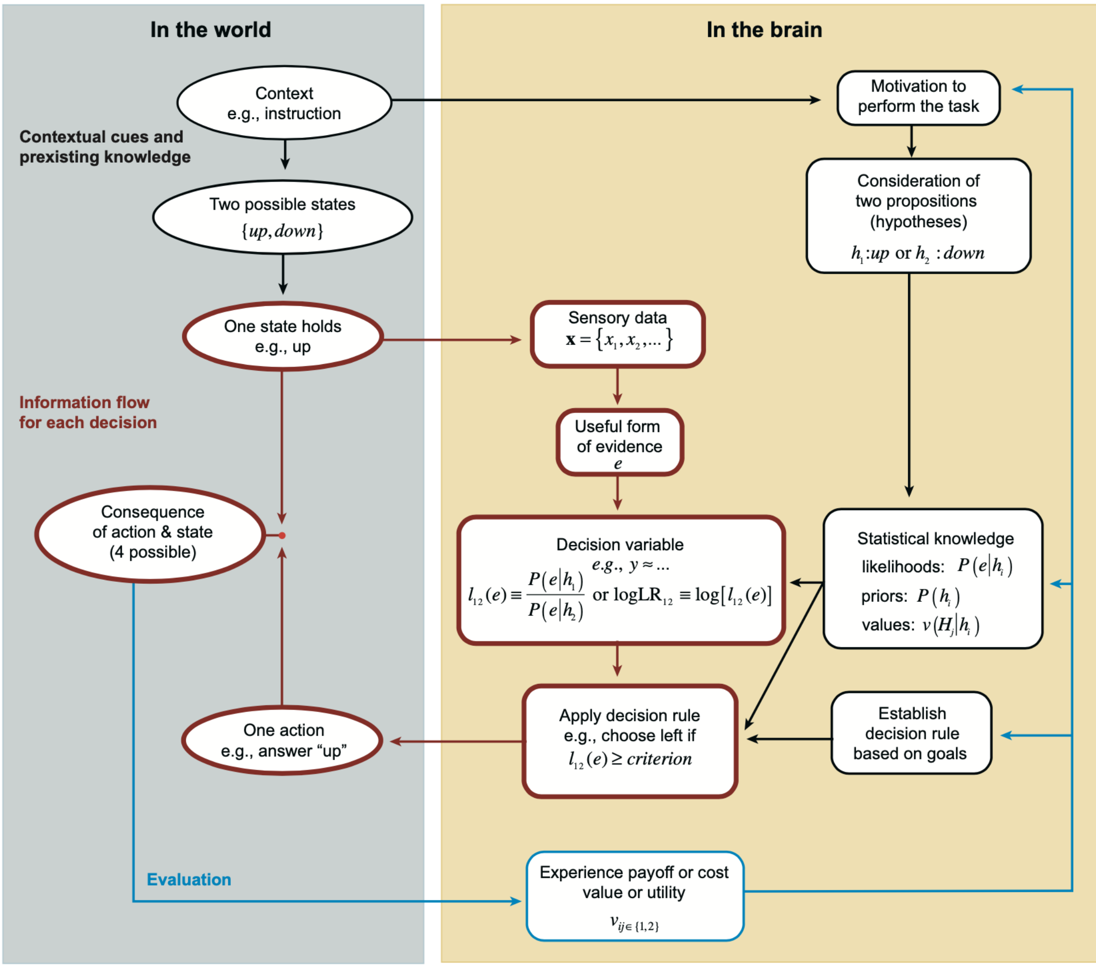


Figure 5: The elements of a decision according to Gold and Shadlen, p. 537 (2007).

walking during time interval t, and U_t is the subjective utility at time t. The time-dependent probability $Pr\{W_t = 1\}$ is the prior for the decision to walk. We expect the prior probability to walk $Pr\{W_t = 1\}$ to be lower than the prior probability to not walk $Pr\{W_t = 0\}$.

$$
\begin{aligned}
p(W_t) \quad &= \tfrac{1}{1+e^{1-U_t}} \\
\textbf{Likelihood:} & \\
W_t \quad &\sim Bernoulli(p(W_t))
\end{aligned}
\tag{2}
$$

Attitude towards walking A_t then serves as what Gold and Shadlen (2007) would refer to as the "value of the decision" (p. 538) including all the benefits an individual might associate with walking. It is supported by reinforcement from walking W_t.[1] The internal and external barriers I_t and E_t correspond to

[1]Interesting enough, the decision framework and the SRC framework describe the same idea here: Just like walking is not only triggered by the stimulus in the SRC framework, the

the context in Gold and Shadlen's (2007) visual. The context is outside of the reallocation process in the brain and merely provides the range of decision options to decide from. Just like availability in JITAI, the internal and external variables I_t and E_t in the decision framework limit the range of options a participant can potentially choose from. However, in Gold and Shadlen's (2007) figure, they are not inherently part of the decision process, but are seen as fixed at time t. Since the SRC model builds on an array of decisions over time, we assume that context and thus the range of decisions is dynamic, too. Thus, we build on the basic structure of their decision model and use context as variables, not as constants, in the model.

Moreover, Gold and Shadlen's (2007) model lacks the influence of past decisions W_{t-1} on the current decision. They are potentially incorporated as priors, but in an array of multiple decisions, their relationship needs to be specified. Therefore, we include the history of decisions and assign different influences to different levels of aggregation. We define the most recent decisions as contributing to the adherence to walk (Choi et al., 2019). If a person has just engaged in a walking bout W_{t-1} or has walked a lot that day already $dayW_t$, the person will be less likely to walk , see section 2.6.

To finally determine the probability of walking, all factors contributing to walking are collected in a utility function U_t for walking, see figure 6. The utility function U_t serves as an immediate desire to walk that fluctuates. The utility of walking at time t is then given by the overall value associated with walking A_t weighed against the availability to walk with I_t and E_t and the factors influencing the adherence to walk W_{t-1} and $dayW_t$.

$$\begin{aligned} U_t \quad = \quad & \gamma_{45}A_{t-1} - (\gamma_{46}I_{t-1} + \gamma_{47}E_{t-1} + \\ & \gamma_{42}W_{t-1} + \gamma_{48}\ dayW_t) + \epsilon_{1,t} \end{aligned} \tag{3}$$

Framing walking inside the decision framework very much fits to the JITAI context. In JITAIs, the right time is not defined as clock time, but as a psychological state (Scholz, 2019; Nahum-Shani et al., 2018). First, the fluctuating utility U_t in this model serves as the psychological state. Then, the dynamical system incorporates a person's availability into the decision which then corresponds to the adherence stage of receptivity for JITAIs (Choi et al., 2019). Taken together,

decision to walk cannot solely be a "perceptual decision" in the decision framework (Sugrue et al., 2005, p. 365). Instead, it is a "value-based decision" (p. 365) driven by the associated value representation, so the reinforcement in the SRC framework (Skinner, 1953).

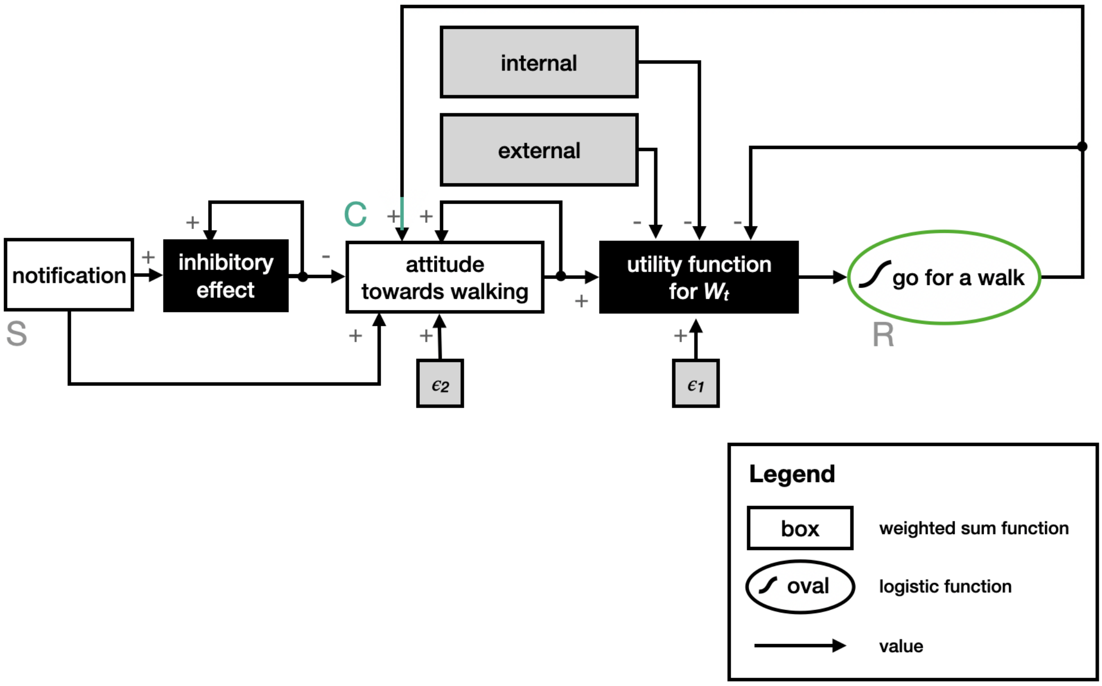


Figure 6: The SRC model adjusted to adherence by mimicking a moment of decision of going for a walk or not going for a walk. Attitude A_t, internal and external barriers I_t and E_t as well as recent walking W_{t-1} and $dayW_t$ influence the decision.

the model strongly represents the idea of JITAIs and can offer a computational model template for any JITAI.

2.6 Modelling different time aggregations

in the JITAI context, it is recommended to divide continuous time into different time scales and to "develop assumptions on interrelations between the variables of interest within and across these different time scales" (Scholz, 2019, p. 9; cf. Nahum-Schani et al., 2018). Depending on the layer of abstraction, one variable, aggregated at different time units, might resemble a variety of constructs (George and Jones, 2000). This is why we introduce three levels of lags for the response walking such that each aggregation refers to a different construct, see the green aggregations in figure 7.

1. **just-in-time as going for a walk:** In line with research on decision-making (Gold and Shadlen, 2007; Sugrue et al., 2005), we operationalize the response walking W_t as a binary walking bout at point in time t, similar to a decision that has been taken. *Walking bouts* have been defined as walking for 10 minutes or longer and are associated with positive health benefits (Glazer et al., 2013; Strath et al., 2008). In the *HeartSteps* intervention,

people have been either nudged to "stand up and do light stretches for 2-3 minutes" and to "take a few minutes" to get up or the suggestions "intended to encourage bouts of 500 to 1,000 steps" (Klasnja et al., 2019, p. 4). Matching the intervention data, we choose t to be 30 minute intervals such that $W_t = 1$ if a person walked for at least 3 minutes or took more than 500 steps in that 30 minute interval. More research is needed to operationalize walking bouts in JITAI contexts.

2. **daily aggregate as a measure of tiredness:** during the course of a day, a person might feel a short-term stock of behavior similar to a stint. If at time t, a person has already walked enough for that day, he or she will be tired and will not adhere to more walking at time t (Choi et al., 2019; Sarker et al., 2014). According to Glazer et al. (2013), on average, participants did one walking bout of moderate to vigorous intensity per day. We introduce the daily aggregate as $dayW_t$.

3. **weekly aggregate as long-term stock behavior:** the median amount of daily walking bouts in the past 7 days. It assesses an overall level of walking and represents more of a general fitness and readiness to walk at time t. Weekly aggregates are a common form of describing general walking behavior (World Health Organization, 2010). We introduce this as $longW_t$.

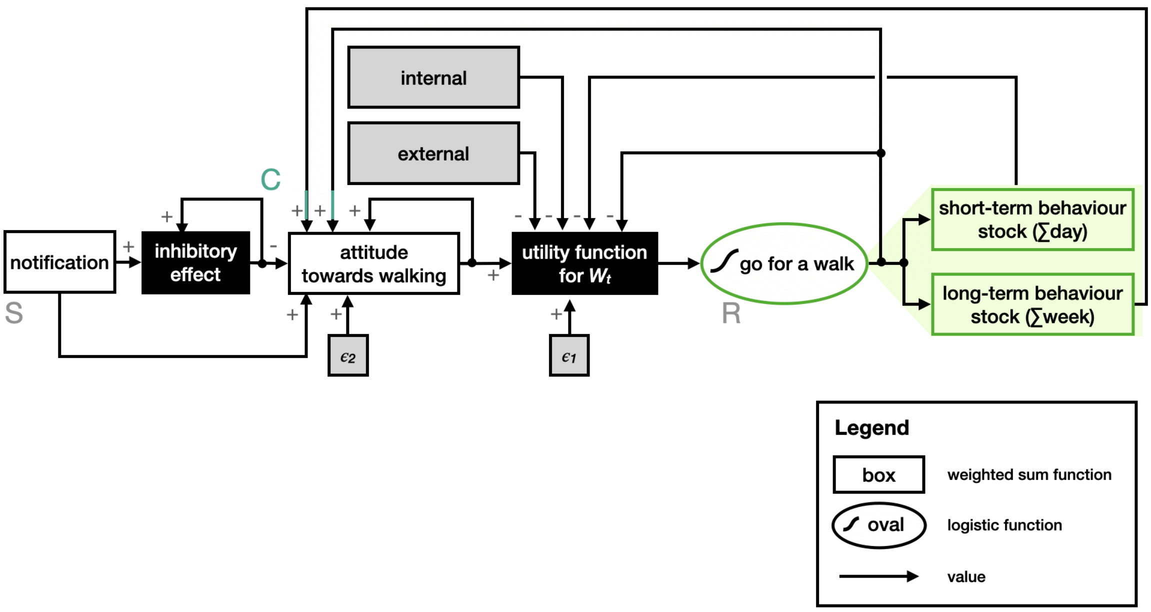


Figure 7: The SRC model including the aggregation of walking bouts on three levels. The full dynamical system includes the threshold, the two exogenous factors, three layers of aggregation of the response walking W_t and its interrelationships.

2.7 Mathematical model

$$t = 0, 1, ..., N \qquad \text{(as 30 min intervals)}$$
$$N = 48 \cdot 40 \text{ days } = 1920 \text{ (slightly varying across people)}$$
$$m_t = t \; mod \; 48 \qquad \text{(time points } t \text{ since midnight)}$$

Input to the system:

$$S_t \in \{0, 1\}$$
$$N_t = \gamma_{11} S_{t-1} + \gamma_{12} N_{t-1} \qquad \text{habituation} \tag{4.1}$$

N=1

The system:

data

output & data

$$W_t \sim Bernoulli(p(W_t)) \tag{4.2}$$
$$p(W_t) = \frac{1}{1+e^{1-U_t}} \tag{4.3}$$
$$U_t = \gamma_{45} A_{t-1} - (\gamma_{46} I_{t-1} + \gamma_{47} E_{t-1} + \gamma_{42} W_{t-1} + \gamma_{48} \; dayW_t) + \epsilon_{1,t} \tag{4.4}$$
$$A_t = \gamma_{55} A_{t-1} + \gamma_{51} S_{t-1}(1 - N_{t-1}) + \gamma_{52} W_{t-1} + \beta_9(\gamma_{59} \; longW_t - A_{t-1}) + \epsilon_{2,t} \tag{4.5}$$

Exogenous Variables:

$$I_t = \sum \gamma_{6i} x_i \quad \forall i \in \text{internal barriers} \tag{4.6}$$
$$E_t = \sum \gamma_{7i} x_i \quad \forall i \in \text{external barriers} \tag{4.7}$$

Aggregating the response:

$$dayW_t = \sum_{i=0}^{m_t} W_{t-i} \tag{4.8}$$
$$longW_t = Median(\sum_{i=0}^{48 \cdot 7} dayW_{t-i})$$
$$\forall i \in m_i = 0 \tag{4.9}$$

Errors:

$$\epsilon_{i,t} \sim N(\bar{x} = 0, \sigma = 0.01) \quad \forall i = 1, 2 \tag{4.10}$$

1. **Input** S_t: the input to the system is a binary sequence of events in time. It describes if a notification has been sent or not. In the operant learning framework, it corresponds to S.

2. **Inhibitory effect** N_t: a linear two-parameter integrator we call N_t, according to Staddon's (2001) 1-unit stimulus-type habituation model.

3. **Response** W_t: the target W_t is a stochastic sequence of independent Bernoulli random variables $W_t \in \{0, 1\}$, and its probability is given by $p(W_t)$. We summarize the amount of steps a participant took within 30 minutes and count it as a walking bout $W_t = 1$ if it lasted 3 minutes or longer or was larger than 500 steps.

4. **Probability to walk** $p(W_t)$: a logistic conversion of the walking utility U_t, a probability that determines how likely it is for a person to engage in a walking bout.

5. **Momentary utility of walking** U_t: a weighted linear utility function for walking with a normally distributed error, a mental calculation before deciding to go for a walk. It serves as an immediate desire to walk that fluctuates. The utility of walking at time t is given by the overall value associated with walking A_t weighed against the availability to walk with I_t and E_t and the factors influencing the adherence to walk W_{t-1} and $dayW_t$ (Choi et al., 2019). If the attitude A_t is greater, U_t is positive and it lifts the prior probability to walk. If the barriers for walking are greater, U_t is negative and it reduces the prior probability to walk.

6. **Attitude** A_t: a weighted function with a normally distributed error, truncated to represent a value between 0 and 1, $A_t \in [0, 1]$. Attitude A_t inherits from past attitudes A_{t-1}, and it is the entity that processes the stimulus, the input notification S_t. Furthermore, it receives reinforcement from past walking experiences, the most recent walking bout W_{t-1} and the long-term walking behavior $longW_t$. The larger the weekly median in $longW_t$ is, the more it will have a positive effect on the attitude. Hence, the more a participant walks, the more he or she develops a positive attitude towards walking A_t, making it more likely for the participant to engage in walking the next time.

7. **Exogenous factors** I_t **and** E_t: weighted sums of internal and external barriers that prevent a person from walking. Both serve as contextual cues

outside of the actual SRC system. If the participant is in a meeting and cannot walk, the external barrier E_t will be positive, adding a barrier to U_t in equation 4.4. If a person is sick or sleeps and cannot walk, the internal barrier I_t will be positive, again adding negative weight to the threshold in equation 4.4. For the simulation, I_t and E_t are drawn from a Bernoulli distribution. Both are heavily biased to stay the way they have been in the last period. If one is sick, one is likely to stay sick at the next point in time, so I_t will likely be the same as I_{t+1}.

8. **Aggregating walking W_t on two additional levels**
    (a) **The daily aggregate $dayW_t$:** the amount of walking bouts taken that day as a measure of tiredness.
    (b) **The weekly aggregate $longW_t$:** the weekly moving median of walking bouts and the longer-term aggregation of the response.
9. **Errors ϵ_t:** normally distributed errors.

2.8 Model considerations

The model makes the following assumptions:

1. All parameters are idiosyncratic and will vary across people while staying constant for each participant.
2. To account for knowledge about the direction of relationships, parameters are positive. Potential positive and negative impacts are specified within the system of equations.
3. The initial values of the parameters are determined by solving the system of equations at steady state, obtaining the following results: $\gamma_{42} = 0.3, \gamma_{45} = 1.8, \gamma_{48} = 0.2, \gamma_{52} = 0.1, \gamma_{55} = 0.9, \gamma_{59} = 0.11, \beta_9 = 0.1, A_0 = 0.5$ We set the influence of internal and external variables to 0.5, $\gamma_{46} = 0.5, \gamma_{47} = 0.5, \gamma_{51} = 0.5$. The gain parameters of the habituation mechanisms will be derived in section 3.1.
4. All γ are gain parameters, determining how important each variable is for the next, β_9 is a rate parameter, corresponding to how fast $longW_t$ changes A_t.

3 Simulating the model

In order to understand and analyze the dynamics that translate into the separation of intervention and internalization, we simulate its behavior using the software R. Complex systems follow nonlinear dynamics with potentially different mechanisms involved (Burger et al., 2020) which we intend to demonstrate using simulation. Thus, we rely on the mathematical specification of our model to be as simple as possible. This allows us to draw generic conclusions that can clearly be attributed to the separation of intervention and internalization and it determines what conditions need to be given for the dynamics to work. In the following, we therefore examine the two dynamics of the separation of intervention and internalization as well as the final decision to walk:

1. The separation of intervention and internalization: the decreasing intervention effect,
2. the separation of intervention and internalization: the internalization and
3. the decision to walk.

3.1 The decreasing intervention effect

3.1.1 Simulating the short-term decrease

The first dynamic we model is the short-term decrease, the decreasing intervention effect (second hypothesized effect). As described above, we follow Staddon's (2001) 1-unit stimulus-type habituation model. In Staddon's model, an increasing amount of stimuli leads to a larger inhibitory effect and a smaller overall impact of the stimulus. Within the dynamical system, we expect it to also lead to a decreasing response after repeated notifications.

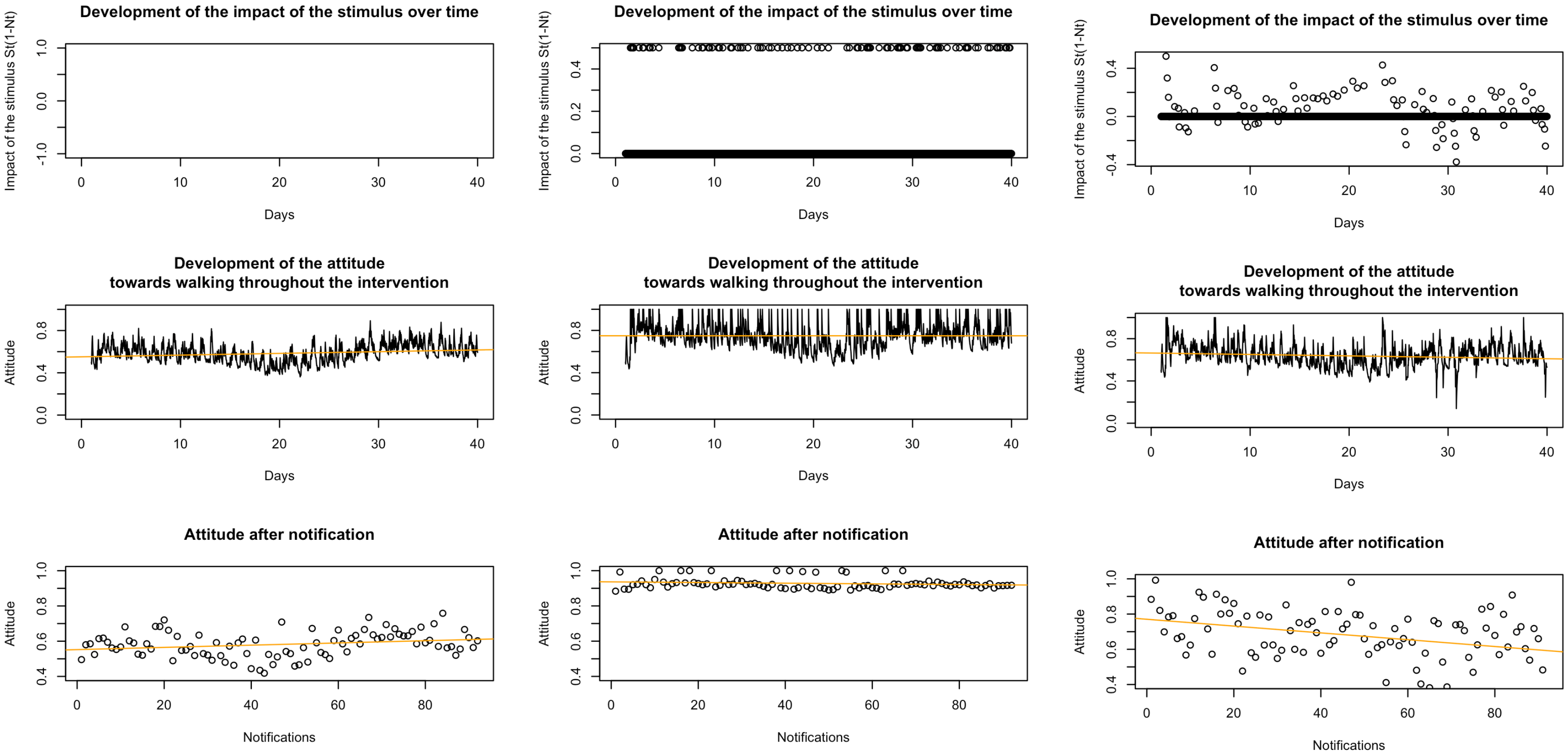
In Klasnja's (2019) analysis, the impact of the notification was 66% and 24% in the beginning, depending on the type of notification sent. To resemble both and stay between them, we set the desirable impact of the notification γ_{11} to 40%. In line with Staddon's (2001) formulation of γ_{12} of around 0.9 (p. 120), we arbitrarily set γ_{12} to be 0.98 such that the inhibitory effect lasts long enough to be visible when sending 2-5 notifications per day (Klasnja et al., 2019). All derived quantities in this simulation will be given for varying γ_{11}s and γ_{12}s, allowing it to be derived for different interventions.

To test the functionality (first hypothesized effect), we first run a control simulation. We employ a one-way analysis of variance (ANOVA) with a control condition without a notification, one treatment condition with a constant stimulus impact and one treatment condition with the proposed habituation pattern activated. Mechanistically, we expect the following to happen: Though the reaction to the notification is decreasing over time, at time t, we anticipate the participant to react by a slight increase in attitude towards walking A_t as compared to A_{t-1}. This influences the decision to go for a walk W_t, hence it is likely that a person will walk after having received a notification. Following habituation, our hypothesis is that with time, this reaction will decrease in the habituation condition. The reaction after S will be greatest when a constant stimulus impact is present and the least without a stimulus. We furthermore expect this dynamic to be most visible in the immediate reaction after the stimulus A_t, not in the overall attitude A_t.

The simulation in figure 8 shows that this expected pattern can indeed be observed in the short-term, the immediate reaction after the stimulus A_t. There is a significant effect of the type of stimulus on the immediate attitude A_t at the p <.001 level for the three conditions ($F(2,\ 273) = 322$, $p < .001$). Post-hoc comparisons using the Tukey HSD test indicate that all mean scores are significantly different, the habituation condition ($M = 0.68$, $SD = 0.15$), the no stimulus condition ($M = 0.58$, $SD = .007$) as well as the constant stimulus condition ($M = 0.93$, $SD = 0.03$).

Specifically, in the habituation condition in the right plots, the participant gets used to the notification and the attitude A_t kicks less and less after a notification over time in the right lower plot, resulting in an 18% decrease throughout the intervention (attitude A_t after notification $= 0.77 - .002$ #S, F =13.08, $R^2 = 0.13$, $n = 92$, $p < .001$), as opposed to a slight increase without a stimulus in the left lower plot (attitude A_t after notification $= 0.55 + .001$ #S,F =5.27 $R^2 = 0.06$, $n = 92$, $p = 0.024$) or with a constant stimulus in the middle lower plot (F =2.32, $R^2 = 0$, $n = 92$, $p = 0.131$).

As expected, the short-term decrease is most visible in the short-term, the immediate attitude after the notification in the lower plots, not in the middle plots. These results suggest Staddon's habituation model can model the short-term response in the decreasing intervention effect.



(a) No notification control condition

(b) Constant notification treatment condition 1

(c) Habituation mechanism treatment condition 2

Figure 8: **Short-term effect of the notification:** To demonstrate the short-term effect of the notification, we plot three different courses of the intervention. The full SRC model including habituation is in treatment condition 2 on the right. Without any notifications on the left, attitude after the notification A_t in the left lower plot reaches a stable level. With a constant impact of the notification in the middle, the attitude after the notification A_t in the lower middle plot regularly hits its maximum possible value. With the habituation mechanism on the right, the attitude towards walking A_t in the right middle plot has a similar trajectory than the three previous conditions, only the attitude after the notification ceases in the right lower plot. The orange line is a linear regression fit.

3.1.2 The ideal intervention based on responsiveness

The habituation model is associated with a sensitivity to frequency (Rankin et al., 2009). If interventionists incorporated thoughts on notification frequency, they could target the decreasing intervention effect and potentially deal with it. Moreover, "spontaneous recovery" describes that participants can react more strongly again after stimuli have taken a break (Rankin et al., 2009, p. 2). From habituation research, it follows that reducing the frequency can bring increase a participant's reaction to the stimulus again such that ultimately, the intervention can be improved and notifications can be sent exactly just-in-time (Nahum-Shani et al., 2018).

More frequent stimuli lead to a stronger decline in the reaction (Rankin et al., 2009). Less frequent stimuli lead to a weaker decline and less habituation, because whenever a stimulus is not present, the participant has time to recover. Mathematically, this can be attributed to the inhibitory effect vanishing during the short recovery period as N_t only inherits parts of what N_{t-1} used to be, $N_t = \gamma_{12} N_{t-1}$ for $S_t = 0$, allowing it to recover as in spontaneous recovery. Hence, the less frequent a stimulus is sent, the higher the impact of S_t can be after recovery. Figure 9 demonstrates this process and shows that the impact of S_t indeed is lower if a stimulus is present more often on the right, where 2-5 notifications were sent per day like in the *HeartSteps* data (Klasnja et al., 2019). The impact of S_t is higher if there is more "spacing" between stimuli on the left, as if notifications are sent daily (Staddon, 2001, p. 119). In order to achieve an ideal intervention, notifications would have to be delivered less frequently, ideally right when a person has recovered from the impact of the notification S_t and is most able to respond to the notification.

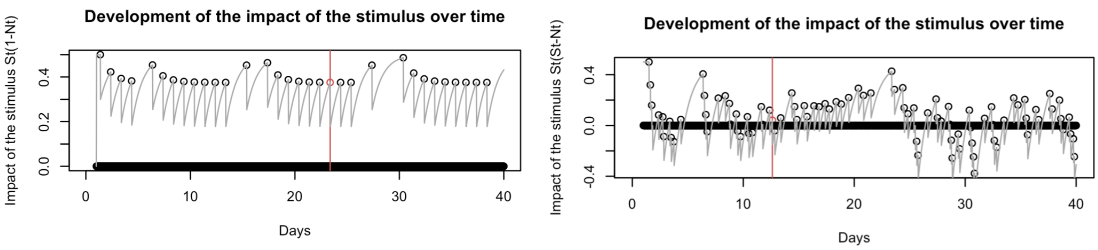


Figure 9: Development of the impact of the stimulus over time. In the right simulation, the stimulus was sent 2-5 times per day like in the *HeartSteps* data (Klasnja et al., 2019). In the left simulation, the notification delivery was randomized on a daily level instead. The grey line depicts the potential impact a stimulus *could* have at t. The actual impact of the notification declines faster if a more frequent stimulus is present. More frequent notifications ($M = 0.15$, $SD = 0.1$) resulted in a 63% lower mean than less frequent notifications ($M = 0.4$, $SD = 0.04$), which was significant at the $p <.001$ level ($t(86.79) = -17.27$, $p <.001$).

To quantify when a person has recovered from the notification, we determine a person's responsiveness for a stimulus. For this, we derive the closed form of Staddon's 1-unit stimulus type habituation model, see equations 4.1 and 4.5, at time t:

$$\begin{aligned} N_0 &= 0 \\ N_t &= \gamma_{11} S_t + \gamma_{12} N_{t-1} \\ impS_t &= \gamma_{51} S_t (1 - N_{t-1}) \end{aligned}$$

In closed form:

$$impS_t = \gamma_{51} S_t (1 - \gamma_{11} \sum_{i=0}^{t-2} \gamma_{12}^i \, S_{t-i-1}) \tag{5}$$

The closed form demonstrates that essentially, the impact of the current stimulus $impS_t$ is always S_t reduced by some inhibitory effect N_{t-1}. Mathematically, this inhibitory effect is a first order dynamical system response which means it is a time-varying exponential smoothing function on past notifications. From this follows that, as expected by the sensitivity frequency in habituation, the impact on S_t $impS_t$ is not only assumed to be dependent on the number of notifications sent, but on the time passed between them as well, γ_{12}^{n-2} at time step n for a notification at $t = 1$.

We define the *potential* impact $impS_t$ if the participant had received a notification at time t as responsiveness, see grey line in figure 9. Following the closed form for the impact $impS_t$ in equation 5, the responsiveness after a notification at $t = 0$ is:

$$responsiveness_t = \gamma_{51}(1 - \gamma_{11} \cdot \gamma_{12}^{t-1}) \tag{6}$$

Figure 9 illustrates how responsiveness can evolve in different ways. A person has recovered from the notification when the grey responsiveness has regained its old level after a short period, mostly on the left, while on the right, a person does not have time to recover from the notification. The responsiveness always follows an asymptotically increasing curve. Figure 10 portrays different trajectories of responsiveness depending on the inhibitory effect on $impS_t$ γ_{12}. Accordingly, in the ideal intervention, a notification would need to be delivered when the responsiveness is reasonably high again.

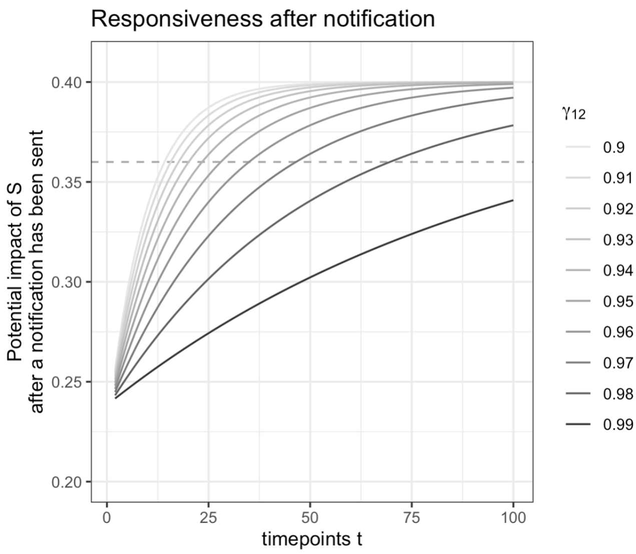


Figure 10: This plot shows ten different trajectories of the asymptotically increasing behavior of responsiveness. The trajectories correspond to different values of the time-varying inhibiting γ_{12}. The dashed line marks the desirable point to send a new notification, 90% of the original impact of S $impS_t$. $responsiveness_t = \gamma_{51}(1 - \gamma_{11} \cdot \gamma_{12}^{t-1})$ with $\gamma_{11} = 0.4, \gamma_{51} = 0.4$.

To ensure a reasonable impact of the digital health intervention, we set that participants need to reach 85-90% of their original responsiveness. Interventionists can of course pick their own desired impact level. We describe the time passed until a participant reaches that responsiveness level as the *recovery period* and derive it by solving for when the responsiveness hits 90% of γ_{51}.

$$0.9\ \gamma_{51} = \gamma_{51}(1 - \gamma_{11} \cdot \gamma_{12}^{x-1})$$

$$\Leftrightarrow \text{recovery period: } x = -\frac{-log(\frac{0.1}{\gamma_{11}}) - log(\gamma_{12})}{log(\gamma_{12})} \tag{7}$$

In figure 10, responsiveness hits 90% of its original value after 10 or even 100 steps in t, depending on the choice for γ_{12}. In the dynamical system as defined in section 2.8, $\gamma_{12} = 0.98$ such that in this intervention, after 70 time steps, the participant would be 90% responsive again. The participant would be at 85% after a day without a notification (49 time steps).

From the definition of responsiveness, it follows that a person that has gotten used to notifications can recover again when no notifications are sent anymore. This means that the decreasing intervention effect is reversible, at least in parts, even for an individual that is heavily unresponsive to notifications like on the right in in figure 9. This finding matches the idea of spontaneous recovery from habituation.

Letting participants take a break and paying attention to the frequency at which an intervention is delivered is an important insight from the decreasing intervention effect. In this section, we illustrated that Staddon's (2001) habituation model can indeed be used to explain a short-term decrease in a digital health intervention. The decreasing intervention effect yielded an 18% decrease in the immediate reaction to the notification.

Certainly, this process is artificial. Following Eysenbach's (2005) law of attrition, one will probably not achieve a constant impact of the stimulus by merely waiting for participants to recover as in figure 9. The recovery period will depend on idiosyncratic parameters and daily notifications are therefore an arbitrary choice dependent on the arbitrary choice of γ_{12}. In addition, recovery periods will likely increase over time leading to participants habituating to the daily notification as well. However, this model sets the framework for future discussions of the decreasing intervention effect. It highlights that notification impacts will likely be dynamic over time, that recovery periods are important and that interventionists cannot assume a constant influence of their intervention. Furthermore, we argue that just like habituation has been incorporated into this model, another equivalent mechanism of an inhibitory effect could be added to account for an increasing recovery period. Following Staddon (2001), one could set up a whole cascade of inhibition. The process could work in the exact same manner, and for complexity purposes, this model only includes the simplified version of habituation.

Still, from the notion of responsiveness, it follows that the timing of a notification is crucial and notifications would have to be delivered when responsiveness has increased again. Waiting for participants to recover contributes to the notification to have the highest effect possible.

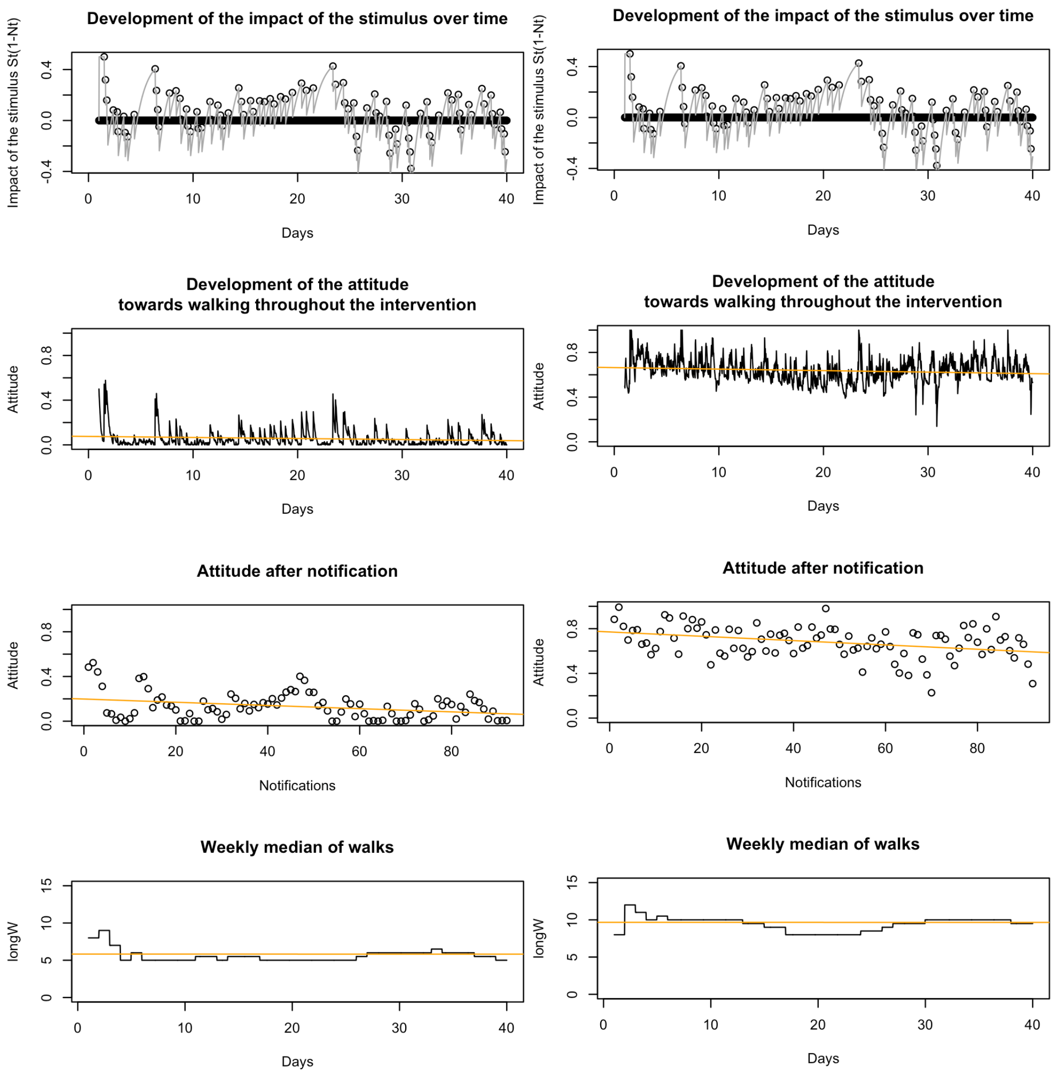
3.2 Separation of intervention and internalization: The internalization

3.2.1 Simulating the constant long-term response

The third hypothesized effect is the separation of intervention and internalization, whereas internalization is the counterforce to the decreasing immediate reaction. As opposed to the short term, the overall reaction does not decrease. Participants potentially build the practice needed to engage in the behavior independently. Mechanistically, we attribute this to reinforcement from walking, the consequence in the SRC model: There are two influences from walking W_{t-1} and $longW_t$ back to attitude A_t, see equation 4.5. The more a participant walks, the more we expect their attitude to increase which enables the overall reaction to be independent from the short-term reaction to S_t.

This behavior can be replicated in the simulation. In a scenario including reinforcement in figure 11, there is a high constant overall attitude A_t (second right plot, $M = 0.64$, $SD = 0.11$) while still allowing the attitude after the notification to decrease (third right plot). In a scenario without reinforcement, the decline due to the decreasing immediate response is visible in a low overall attitude A_t (second left plot, $M = 0.06$, $SD = 0.08$), not just in the attitude after the notification A_t as intended (third left plot). In the left plots, the decreasing reaction to the notification dominates the system's behavior and the overall response is barely independent from S. Reinforcement from walking is therefore crucial for a high overall attitude A_t, the difference in overall means across the two conditions is significant on the $p <.001$ level ($t(3423.71) = 192.58$, $p <.001$).

These results indicate that incorporating a reinforcement mechanism from walking enables a constant long-term response independent from S. As this is the necessary second part of the separation of intervention and internalization, it follows that the SRC framework and this adjusted model can indeed account for this effect. Its habituation model for S and the reinforcement mechanism from C allow the overall reaction to be independent from the from the notification S_t.



(a) No reinforcement control condition

(b) With reinforcement treatment condition

Figure 11: **Long-term effect of the intervention:** Over the course of the intervention, a participant is simulated to have reinforcement from walking (right) and without (left). Left: $\gamma_{52} = 0, \beta_9 = 0$.

3.2.2 Differentiating between short- and long-term reinforcement

While both reinforcing influences W_{t-1} and $longW_t$ contribute to the independence of the long-term response, the weekly median is especially important for this process, see figure 12. This figure visualizes how the overall system evolves if the influences of long-term or short-term reinforcement change respectively. Each plot collects the results of 80 system simulations with different values for γ_{52} and β_9. The plots give insights to what a meaningful range for both parameters could be. A range for meaningful β_9 values that still impact the system is $\beta_9 \in [0.01, 0.2]$, the range for meaningful γ_{52} values is $\gamma_{52} \in [0.01, 0.8]$. The plots

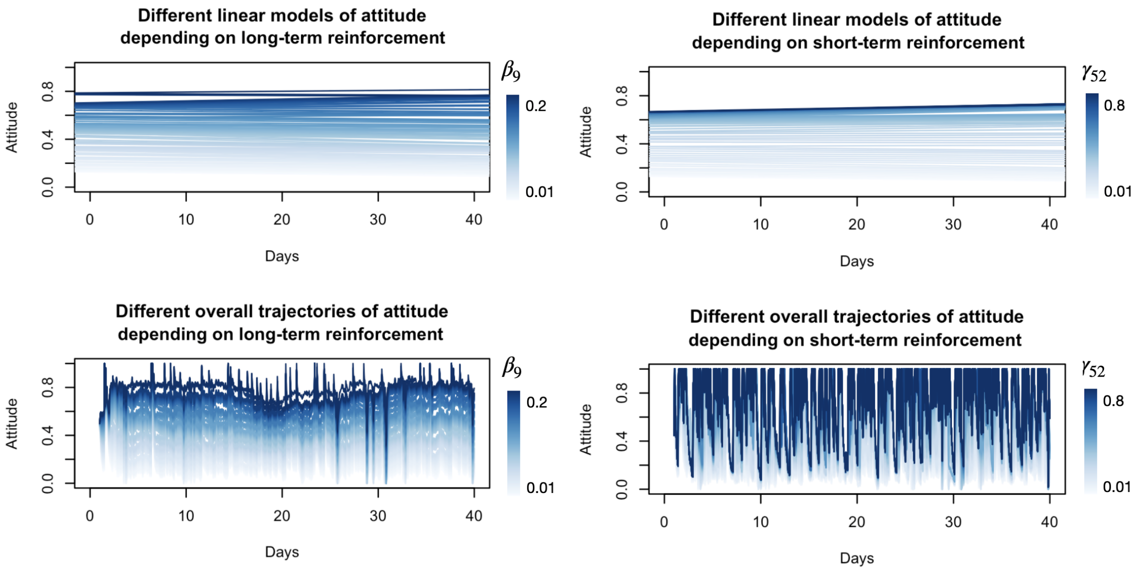


Figure 12: Long-term influences from walking leads to a stable trajectory of the attitude A_t (left), the short-term influence mostly creates more variance in attitude A_t (right). The top plots display the linear models of attitude A_t, the lower plots the overall trajectories of A_t for the 80 dynamical systems with different parameter sizes for β_9 and γ_{52}.
Left: $\beta_9 \in [0.01, 0.2], \gamma_{52} = 0.01$. Right: $\beta_9 = 0.01, \gamma_{52} \in [0.01, 0.8]$.

demonstrate that the stronger the reinforcement and the higher their parameters γ_{52} and β_9, the more they lift the overall level of the system, see the upper plots in the figure.

However, although a higher influence γ_{52} of the most recent walking experience W_{t-1} leads to a higher attitude A_t, see upper right plot, it mostly generates more variance within attitude A_t and cannot create a stable overall trajectory, see the lower right plot. The long-term behavior stock $longW_t$ on the other hand constantly influences the attitude A_t and enables an overall increase of attitude A_t, see upper left plot. At the same time, the variance in attitude A_t does not rise with an increase in β_9, see lower left plot. Consequently, the slower process of $longW_t$ is crucial for the reinforcement from walking in the dynamical system to work as it can create the steady overall reaction the faster process W_{t-1} cannot.

3.2.3 The ideal intervention based on impact duration

When the decreasing intervention effect is present, reinforcement from walking can keep a stable attitude A_t, but is not able to increase it (overall attitude A_t= $0.79 + 0\ t$, $F = 22.51$, $R^2 = .01$, $n = 1873$, $p < .001$) in the right plot in figure 11. Nonetheless, as already established, there is means to conquer the decreasing intervention effect. In an ideal intervention, notifications could be delivered just so the participant is responsive again after a certain recovery period with less of a decreasing short-term response, see section 3.1. In figures 13 and 14, such an ideal intervention is plotted. Notifications are sent daily instead of multiple times per day and the participant seems to be responsive to the impact of the stimulus, keeping a constant high impact of the notification. This means that in this artificially ideal setting, reinforcement can indeed increase the overall attitude A_t, by 20% in this case ($A_t = 0.52 + .005\ t$, $F = 503.96$, $R^2 = 0.21$, $n = 1873$, $p < .001$ and $A_t = 0.597 + 0.005\ t$, $F =$407.568, $R^2 = 0.179$, $n = 1873$, $p < .001$), see left lower plots in figures 13 and 14.

These two systems manifest that, as established, the timing of a notification delivery is important to allow for a recovery period between stimuli. However, how in response the behavior develops depends on a different factor, the duration of the notification impact. These two intervals sound similar, yet, the recovery period and the duration of the impact are two separate time intervals: after receiving a notification, a participant might be more fascinated by walking, raising attitude A_t. Already an hour later, they maybe do not remember the message in particular and have a lower attitude towards walking A_t, but could still be annoyed if a new notification came and would not react to it. This is shown in the first system in figure 13: the recovery period in the top right plot is fairly long, while the impact of the stimulus has a much shorter duration (lower right plot). In the second system in figure 14, the duration of the impact is a bit longer in the lower right plot, but still different from the recovery period (upper right plot).

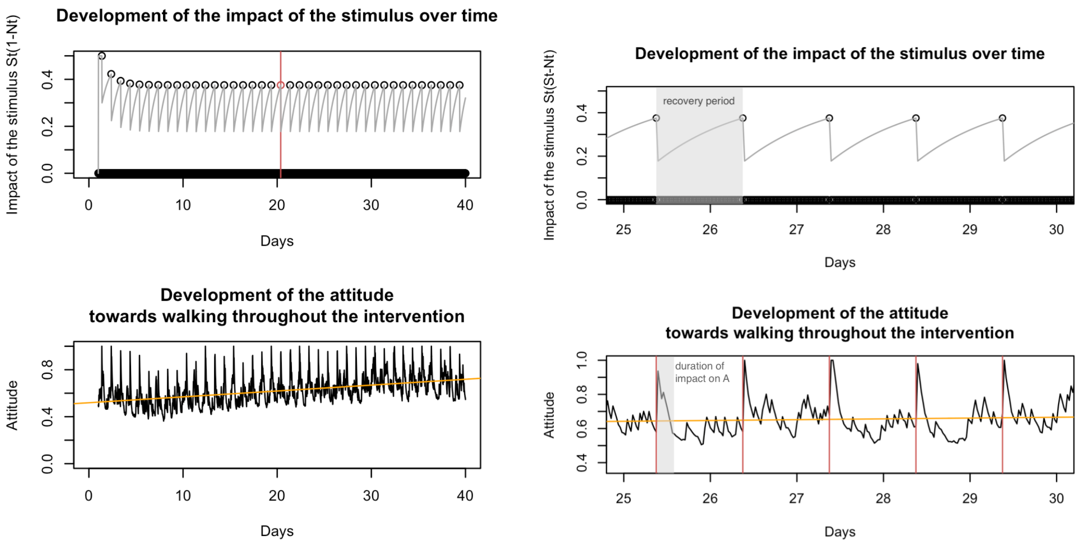


Figure 13: When notifications are sent daily, reinforcement from walking can create a 20% increase in attitude ($A_t = 0.519 + 0.005\ t$, F =503.955, $R^2 = 0.212$, $n = 1873$, $p < .001$, $SD = 0.122$, length of recovery period $= 49t$, length of stimulus impact $= 5t$).

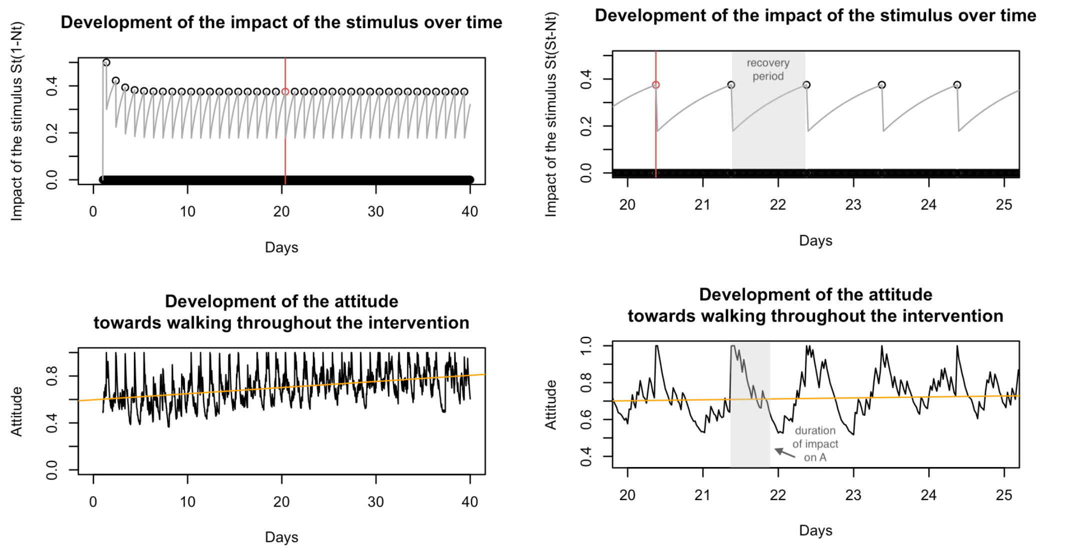


Figure 14: Daily notifications and a very strong influence from $longW$ can increase the duration of the notification impact, but cannot quite align it with the recovery period ($A_t = 0.597 + 0.005\ t$, F =407.568, $R^2 = 0.179$, $n = 1873$, $p < .001$, $SD = 0.14$, length of recovery period $= 49t$, length of stimulus impact $= 12t$, changed parameters for $longW_t$: $\beta_9 = 0.005, \gamma_{59} = 1$).

To facilitate an understanding of what influences this duration of the notification impact, we calculate the impact duration after a notification has been sent at time t. First, given a stimulus at t, the attitude A_{t+1} at time $t + 1$ changes. To return to the old value A_t before a notification after x time steps, we set

$A_{t+x} = A_t$. We furthermore use that without any influence from past walking and no stimuli, the closed form for A_t is $A_t = \gamma_{55}^t A_0$. If we then assume a daily notification, the *impS* after a recovery period is $0.85\,\gamma_{51}$ and the raw duration of the impact is:

$$\begin{aligned} A_{t+x} &= A_t \\ \Leftrightarrow \text{duration of impact:} \qquad x &= \frac{log(A_t) - log(\gamma_{55} A_t + 0.85\,\gamma_{51})}{log(\gamma_{55})} + 1 \end{aligned} \tag{8}$$

The duration that is also pushed by the reinforcement from walking lasts slightly longer:

$$\Rightarrow \text{including } longW_t\text{: } x = \frac{log\Big(\frac{A_t(\gamma_{55} - \beta_9 - 1) + \beta_9 \gamma_{59} 8}{A_t(\gamma_{55} - \beta_9 - 1) + 0.85 \gamma_{51}(\gamma_{55} - 1) + \beta_9(\gamma_{59} 8 - 0.85 \gamma_{51})}\Big)}{log(\gamma_{55} - \beta_9)} \tag{9}$$

Following this, the notification impact is six points in time (3h) in figure 13, and 12 points in time (6h) including strong reinforcement in figure 14, assuming the daily median is 8 bouts/day, see the lowest plots in figure 11. Still, both notification impacts are shorter than the recovery period: it takes 49 time steps to recover in both two systems, while the notification impact duration is six or 12 time steps respectively.

As described above, handling the decreasing intervention effect by being mindful of the recovery period can create an overall increase in attitude A_t. Adding the notion of the duration of the impact on top, an intervention could accumulate an even higher increase. If in the right moment, both the recovery period and the duration of the stimulus were aligned, the person could be responsive again *and* the impact of the notification would still be influencing A_t. Every time a notification is sent, the attitude would then be higher than the last time a notification was delivered, allowing an accumulation behavior to build up, see figure 15.

For these two intervals to align, one solution is to only define a small recovery period (system solved for a small inhibitory effect $\gamma_{12} = 0.68, A_t = 0.6$ or a small impact of the stimulus $\gamma_{51} = 0.07, A_t = 0.6$), meaning people are quickly responsive again. Underestimating the recovery period however defeats the purpose of this model. Increasing reinforcement from walking in the system on the other hand does not yield satisfactory results either. Analytically, there is no solution and figure 14 shows that even a very large walking reinforcement is not large enough to align with the recovery period. An alternative solution would be to assume a longer lasting lag of the notification, so enabling the stimulus S_t to operate for longer than one point in time. As an example, a thought-provoking stimulus could lure people into checking back with the notification or fulfill a

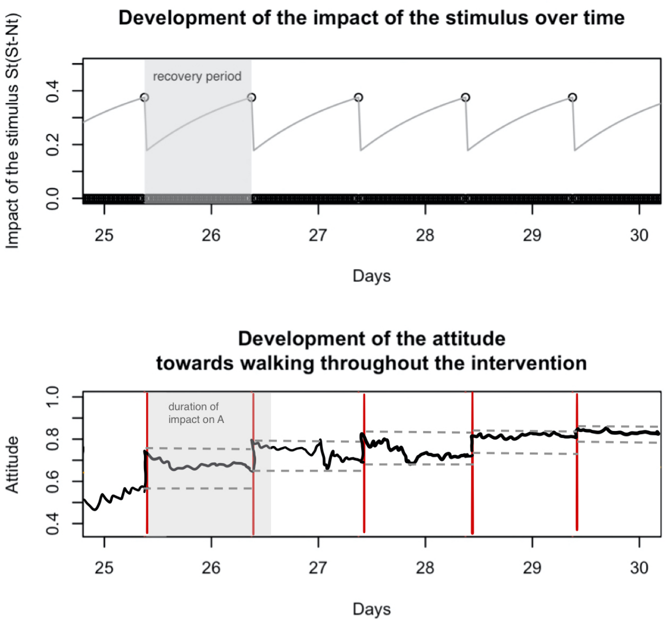


Figure 15: A hypothetical system in which the recovery period and the duration of the impact of the notification are aligned. In this system, the attitude towards walking A_t would not even fall below the old level any more and would exhibit a constant accumulation behavior. The current system cannot account for this.

small task that extends the length of the stimulus effect. The current system based on the *HeartSteps* intervention does not include such a long impact of the stimulus. The system in figure 15 is therefore only hypothetical.

As this section kept exploring the decreasing intervention effect, it became important to ensure people's responsiveness in the ideal intervention. Warranting the person has had a sufficiently long recovery period enables a larger impact of the notification and supports internalization, such that the dynamical system increases by 20% already. In an even more ideal intervention, one would have to align people being responsive with the duration of the notification impact. The current system cannot model this behavior, yet future interventions could start experimenting with ways to raise the impact duration of the notification.

3.3 The decision to walk

3.3.1 Simulating availability and the decision to walk

After having analyzed the dynamics tied to the separation of intervention and internalization, we focus on the last integral part of this model: We introduced the target walking as a binary decision. Walking depended on the linear utility function for walking U_t that mirrors an immediate desire to actually engage in walking. U_t included the attitude A_t as a value that is compared against potential barriers. These barriers were the availability factors I_t and E_t as well as the adherence factors W_{t-1} and $dayW_t$:

$$U_t = \gamma_{45} A_{t-1} - (\gamma_{46} I_{t-1} + \gamma_{47} E_{t-1} + \\ \gamma_{42} W_{t-1} + \gamma_{48}\ dayW_t) + \epsilon_{1,t}$$

By framing walking as a decision process, the moments *when* a person actually engaged in walking became crucial. Linear models can potentially employ a strategy to push internal reasons for walking. Even if external availability variables such as "being in a meeting" are high, pushing a person can still generate an *increase* in steps (from a model perspective). Binary models on the other hand have to shift the intervention focus from increasing the amount of steps towards enabling those situations when a person actually walked. If a person is not available, the final decision to walk will not be low but no walking at all, matching the idea of just-in-time in JITAI (Nahum-Shani et al., 2018).

Consequently, we analyze what drives the moments when a person engages in walking. First, in this model and in the JITAI context, a substantial part to these are a person's availability (Choi et al., 2019). When a person is not available, they do not engage in walking either. In the simulation, the model can indeed reproduce this, an unavailable person is much more unlikely to walk, see left plot in figure 16, as compared to when a person is available on the right. The simulation demonstrates that the adherence functionality works, too. Without the daily aggregate $dayW_t$, people keep walking at the end of the day instead of ceasing to walk, see figure 17. The fluctuations in $p(W_t)$ in the top plots mostly refer to availability.

These simulations illustrate how the decision to walk is a mechanism to consider the JITAI components availability and adherence: if either of them is high, the probability to walk will be rather low, allowing the utility U_t to be a reasonable estimate of a good just-in-time moment.

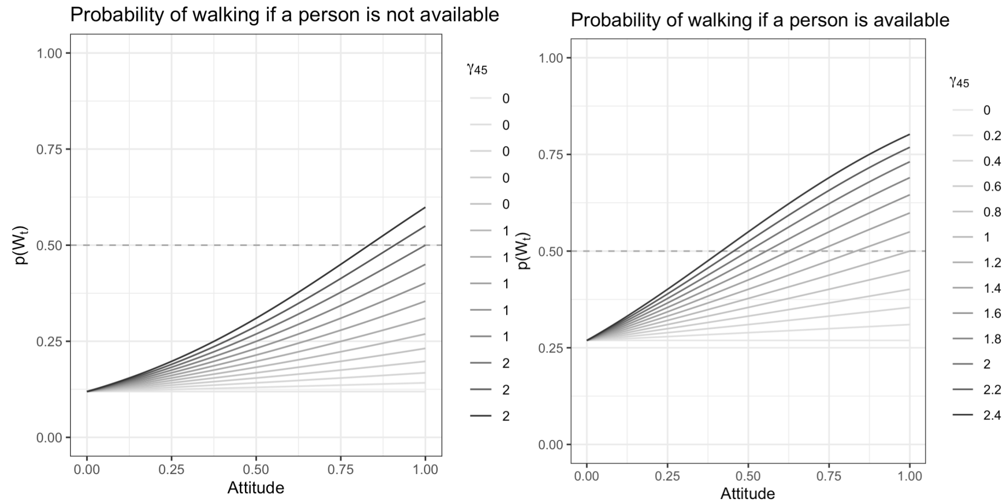


Figure 16: When a person is not available, they will be much more unlikely to walk (left) as opposed to when available (right). This follows the availability concept in JITAIs (Choi et al., 2019). The curves correspond to different segments of the logistic function for $p(W_t)$. Even a very strong impact of the attitude γ_{45} paired with a high attitude in that moment is very improbable to trigger a person to walk.

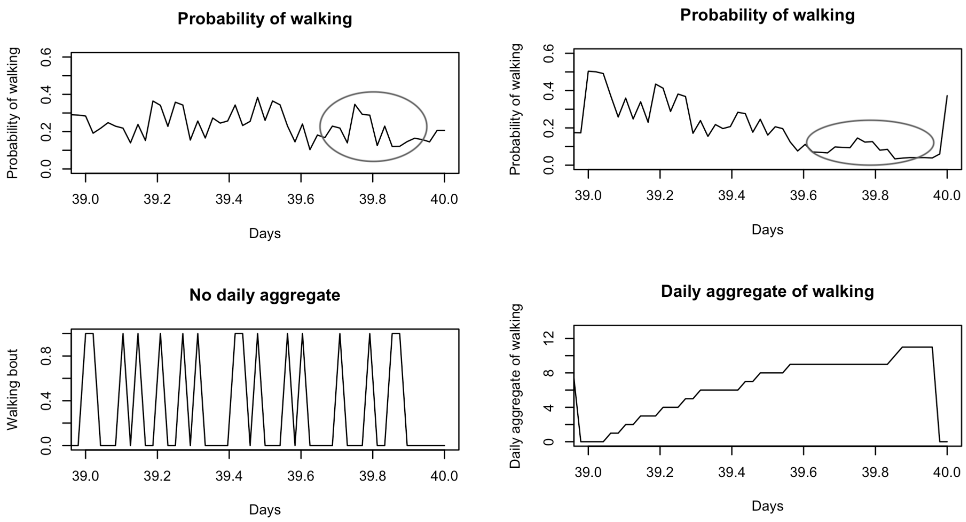


Figure 17: When taking a daily aggregation of walking into account, the probability of walking $p(W_t)$ drastically decreases at the end of the day. In the right plot, the probability for walking $p(W_t)$ declines the more a person has walked, in the left plot, it does not.
left: $dayW_t = W_t, longW_t = W_t$.

3.3.2 The ideal intervention based on a customized delivery

After having discussed responsiveness and the duration of the notification impact, the last consideration for an ideal intervention derived from this model is to tailor the intervention to those moments in which it is also likely for a person to walk. In JITAIs, a notification is essentially wasted if a person cannot walk in that given moment (Nahum-Shani et al., 2018). Hence, for a high impact of the notification, an interventionist would have to send a notification when a person is responsive, available and likely to adhere. This mirrors the idea of *adaptation*, the "use of ongoing (dynamic) information about the individual to modify the type, amount, and timing of support" (Nahum-Shani et al., 2018, p. 448).

In figure 18, we simulate how a notification is sent at a customized time point. It is delivered when two criteria are met. First, a person's responsiveness needs to be at a minimum 85% again (grey in the upper left plot). Second, the person needs to be available and likely to adhere. We operationalize this as the probability to walk $p(W_t)$ being highest within 24 hours (black in the upper left plot). Only when both criteria are fulfilled, a notification is delivered. For the standard daily notification, the delivery time point is arbitrarily chosen. The simulation shows that a person indeed walks more after a customized delivery (lower left plot). In the standard delivery case, a high probability to walk and the notification time point do not necessarily align (upper right plot). Walking after that notification then proceeds to be fairly low ($M = 1.31$, $SD = 0.95$) (lower right plot). After the custom notification, a person will engage in a significantly higher amount of walking bouts ($M = 3.12$, $SD = 0.96$), which is significant on the $p < .001$-level ($t(27.78) = 6.41$, $p < .001$).

In conclusion, the last layer of improving the intervention is to ensure the notification is sent just-in-time: the probability for walking $p(W_t)$ is high, a person is both available and likely to adhere to walking. Future JITAIs can follow this example and tailor the notification delivery by evaluating what the decision process would look like in that very moment.

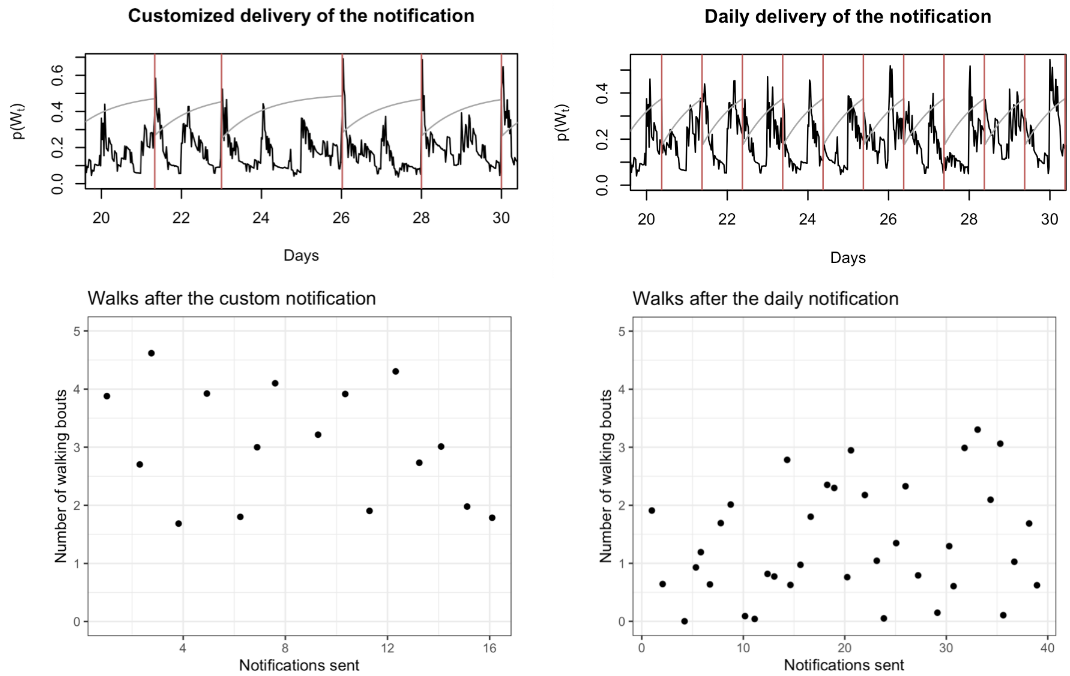


Figure 18: A comparison of a customized notification delivery as opposed to a standard daily notification. On the left, notifications are only sent if 1) responsiveness is at least back up at 85% and if 2) the probability for walking $p(W_t)$ is highest since 24 hours. The difference in walking after the notification for the customized delivery ($M = 3.12$, $SD = 0.96$) and the daily delivery ($M = 1.31$, $SD = 0.95$) is significant on the $p < .001$-level ($t(27.78) = 6.41$, $p < .001$).

4 Model estimation via secondary analysis

The simulations have explored the dynamics of separation of intervention and internalization and what role tailoring an intervention delivery has. Next, the parameters need to be estimated idiographically for each participant. We choose a Bayesian estimation with MCMC sampling to match the probabilistic decision framework (Gold and Shadlen, 2007). The target of the Bayesian model is W_t, a binomial random variable, and its probability is given by $p(W_t)$, leading to the likelihood to walk being Bernoulli-distributed. We estimate the model using Stan in R, running four chains in parallel.

$$\begin{aligned} p(W_t) \quad & = \tfrac{1}{1+e^{1-U_t}} \\ \textbf{Likelihood:} & \\ W_t \quad & \sim Bernoulli(p(W_t)) \end{aligned} \tag{10}$$

The model has the following dependencies:

$$\begin{aligned} U_t \quad & = f(A_{t-1}, W_{t-1}, dayW_t, X1, X2, \epsilon_{1,t}) \\ A_t \quad & = f(A_{t-1}, N_{t-1}, W_{t-1}, longW_t, X1, X2, \epsilon_{2,t}) \\ N_t \quad & = f(N_{t-1}, X3) \\ dayW_t \quad & = f(W_t) \\ longW_t \quad & = f(W_t) \end{aligned} \tag{11}$$

with $X1$ as data for I_t, $X2$ being data for E_t and $X3$ corresponding to S_t. The parameters all follow a flexible Beta prior, $\gamma_{ij} \sim Beta(1,1) \quad \forall i,j$, and the errors are normally distributed, $\epsilon_{ij} \sim N(0, 0.01) \quad \forall i,j \in \{1,2\}$.

4.1 The data

The *HeartSteps* data is used as $X1$, $X2$ and $X3$ in the estimation process. For internal and external barriers $X1$ and $X2$, a number of variables can determine availability. First, high stress levels add to unavailability (Sarker et al., 2014), as does any location that is not home, work or recreational (Choi et al., 2019). People that are in transit or driving are also not available (Sarker et al., 2014). Furthermore, bad weather conditions such as high temperature and precipitation are considered as barriers to physical activity (Tucker and Gilliland, 2007). In addition, in the *HeartSteps* intervention, participants reported individual barriers towards walking such as "traffic" or "sickness" on a daily basis (Klasnja et al., 2019). Lastly, participants had the opportunity to respond to a walking suggestion with "thumbs up" or "thumbs down". All these variables are used to derive internal and external barriers I_t and E_t. The variables used in this estimation are reported in the appendix and all columns of the *HeartSteps* data have been documented in a ReadMe (Gotzian, 2020).

This dataset's key issue is that variables were not recorded continuously. For internal barriers I_t and external barriers E_t, the *HeartSteps* data only provides data at three time points, the daily ecological momentary assessment (EMA), when walking suggestions are sent and when a person replied to walking suggestions. Only then, the GPS used to determine weather is recorded, a person's location is determined using Google place types ("DetectedActivity | Google APIs for Android | Google Developers", 2019) and the activity of a person is inferred ("Place.Type | Places SDK for Android | Google Developers", 2020). On average, there are 175 availability data points per person ($SD = 59$). To augment the existing dataset, questions asking for a daily level of eg. the barriers are extended to the entire day. The target walking W_t is the only data that is available for all time points. The scarcity of the data discounts the possibilities to estimate a full dynamical model. We therefore present a strategy how to estimate the parameters and acknowledge that the generalizability of the model will have to be assessed in future studies. Additionally, we clearly specify how future interventions would need to be altered in order to ensure this model's validation.

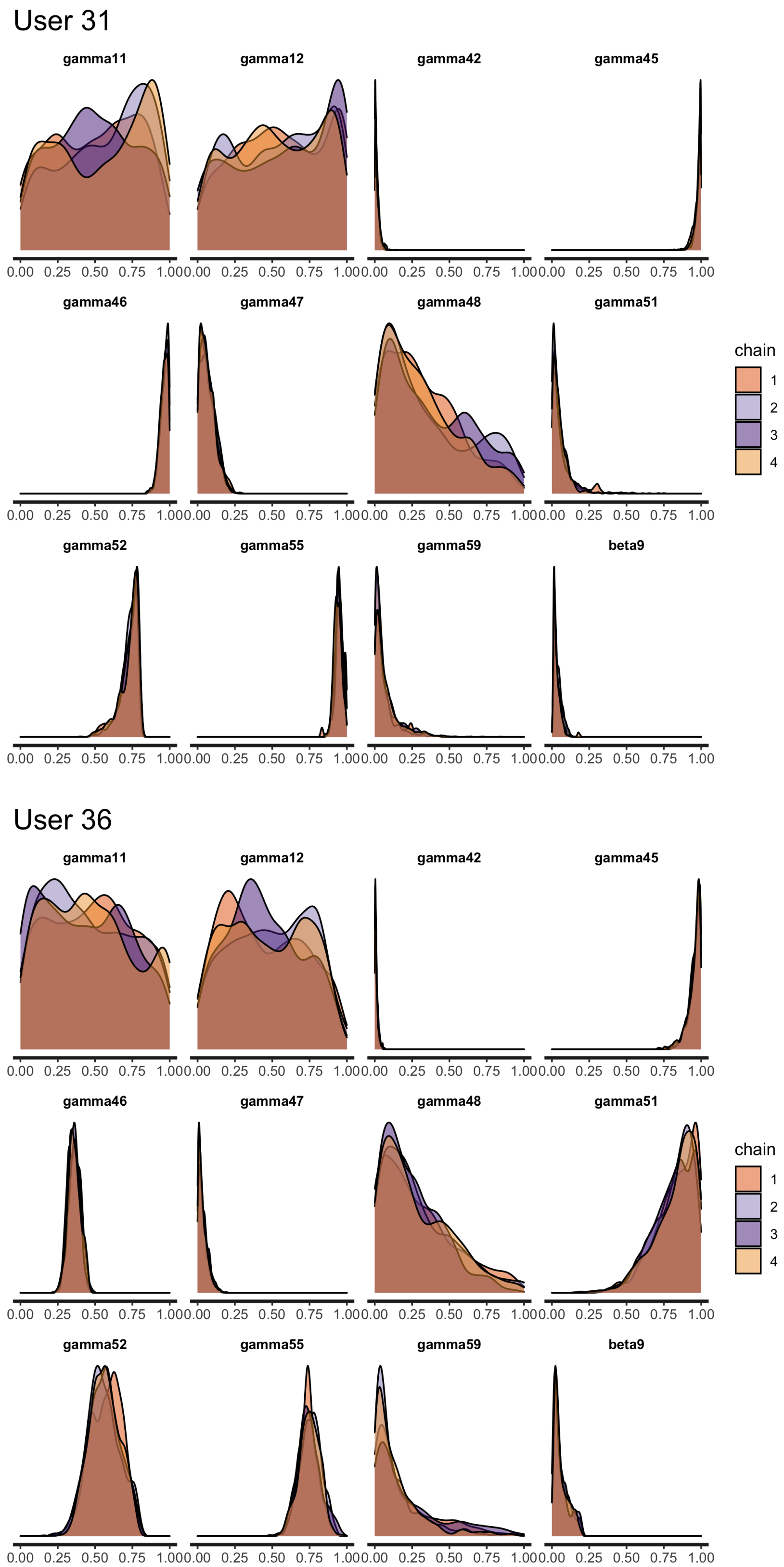


Figure 19: The estimates of the parameters after running 4 chains for 2000 iterations in Stan for participants 31 and 36 that were chosen arbitrarily.

4.2 Results

The estimation shows possible values for each parameter for participant 31 and 36, see figure 19. For these two users, the chains converge for nine of the twelve parameters. In line with this model's target on idiosyncratic behavior, the impact of internal and external barriers γ_{46} and γ_{47} converged and differ across the two users, as does the reinforcement of immediate walking γ_{52}. The impact strength of the notification γ_{51} and the inheritance of past attitudes γ_{55} also seem to be idiosyncratic. Though it mixed well across the chains, the unavailability impact of the most recent walk γ_{42} does not seem to have an influence for any of the users, and the longterm reinforcement γ_{59} and β_9 is rather low for both, though not 0. Unfortunately, the missing data is apparent for the habituation parameters γ_{11} and γ_{12} as well as the daily capacity γ_{48}. All three parameters do not converge well. In general, the current estimation of walking, as expected, rarely beats the very high baseline prevalence of not walking ($M = 81.6\%$, $SD = 6.3\%$), making more data inevitable.

4.3 Considerations for future studies

For future studies, the estimation demonstrates three important aspects: the exact definition of walking bouts, a continuous timeline and additional measurements. First, the definition of walking bouts becomes important. We proposed that a person is unavailable if he or she walked in the last time period (Choi et al., 2019), however in this model, the most recent impact of W_t γ_{42} seems to have no effect. One explanation could be that a person already not engaging in walking because he or she has already gone for a walk is not as relevant for short walking bouts. For longer walking bouts of >10 minutes, the unavailability after a recent walk could still hold true, yet for these short walking bouts, the estimation indicates it does not. The exact definition of a walking bout therefore becomes crucial, as different lengths could imply different associated behaviors.

The second aspect is the importance of a continuous timeline, as opposed to data collections only at decision points in JITAIs (Nahum-Shani et al., 2018). First, a continuous timeline is crucial to validating the functionality of this model's internalization mechanism that is independent of decision points. Moreover, it would allow for more data than approximately 175 data points per person. Furthermore, the parameters needed in the habituation processes γ_{11} and γ_{12} do not yield interpretable results, the chains don't converge for these two parameters. On average, participants received 106 notifications throughout the intervention

($SD = 15$) which are not enough data points to assess a meaningful pattern of habituation.

To enlarge the dataset while (i) ensuring an idiosyncratic estimation as well as (ii) not sending even more notifications over longer periods of time, we propose assigning individuals to clusters that are then estimated collectively. One clustering method for this is soft K-Means based on similarities (Stan Development Team, 2018). Each person $n \in \{1, ..., N\}$ is randomly assigned to a cluster $z_n \in \{1, ..., K\}$, $z_n \sim categorical(1/K)$. In the Bayesian clustering process, the probability of each user's data y_n follows a multivariate normal distribution with a mean of the assigned cluster mean μ_z and a fixed unit covariance matrix Σ_z, $y_n \sim N(\mu_{z[n]}, \Sigma_{z[n]})$. This gives a likelihood of half the negative Euclidian distance from the cluster mean μ_z to the data point y_n. Eventually, soft K-Means returns clusters with those data points that have minimum Euclidian distance to their cluster mean μ_z. The SRC model could then be validated with sets of similar users that were assigned to the same cluster. At the same time, each estimation would have higher validity as it utilizes more data points. Clustering in return requires sufficient data for each cluster, longitudinally by a continuous collection of data points such that clusters can be built in the first place based on similarity, and laterally by more participants in general such that each cluster has a meaningful number of users assigned to it. The *HeartSteps* data included 37 participants that are sought to be treated idiosyncratically (Klasnja et al., 2019). As a rough estimate, if we assume half as many groups $K = 20$ with on average 10 participants of 106 notifications each, the intervention requires 200 participants.

Lastly, the data that is fed to the model comes from availability considerations $X1$ and $X2$, from the notification $X3$ and from current and past walking. Especially internal and external barriers I_t and E_t could be measured more rigorously and more explicitly. New data could incorporate a clear collection of life circumstances that work as barriers such as "writing a thesis", "being sick" or "being in quarantine", to name a few examples. Continuous monitoring of a person's sleep via wristbands will also be essential. Depending on the intervention type, further research on what belongs to the availability variables internal I_t and external E_t is required. To determine the essential availability variables for their intervention type, interventionists could ask open questions on what people perceived to be decisive when they were unavailable for walking. These could be collected in a daily EMA. On top of that, questions like "Are you available to stand up and move?", "Why do you (not) stand up and move around for a minute?" and "Please describe your context" could be asked with each notification (Choi et al., 2019, p. 10). Hypothetically, the variables assigned to internal and external barriers should all show a similar barrier behavior and serve as switches when it comes to the threshold to walk.

To validate the more intermediate compartments within this model, they will have to be measured regularly as well. For attitude towards walking A_t, one could send a rating question with each notification sent, asking ”How do you like walking?”. At the same time, the impact of the daily aggregation of walking could be assessed. For $dayW_t$, one could ask how tired a person is in regards to having walked a certain amount of steps that day. Measuring these intermediate compartments like attitude will benefit the validation of the model as a whole.

Taken together, even if the estimation itself cannot yield sufficient results, it sheds light on how a suitable dataset would need look like. Such a larger and more meaningful dataset should enable researchers to validate the proposed SRC model to a much larger extent and gain sufficient insights to the usefulness of each compartment.

5 Discussion

This work first intended to shed light on the separation of the decreasing intervention effect and an internalization process. It offers a robust structure that can be adapted for other intervention types. Second, it is supposed to advance the notion of JITAIs by offering a clearly specified dynamic hypothesis and computational model of a digital health intervention for walking suggestions.

First, this dynamical model offers a robust structure for any intervention type based on the learning framework SRC aiming to model a separation of intervention and internalization. We deem the model to be successful if it can be useful in context. It therefore is kept generic enough to be adapted to the intervention type. As a key mechanism, this model provides an approach to treat both the decreasing intervention effect and the idea of building practice of the desired behavior over a longer period of time. The immediate decreasing intervention effect follows a habituation mechanism (Rankin et al., 2009; Staddon, 2001) and internalization follows the concept of reinforcement for building practice (Skinner, 1953). schraefel (2020) proposed interventions to build practice, but also skills and knowledge. Just like practice is built by using a reinforcement mechanism in this SRC model, skills and knowledge could be internalized by slowly filling a separate compartment over time. As an example for building self-management skills, an intervention could be aimed at teaching people how to plan ahead. If they realize they'll have time in the next few hours, they could integrate a walk into their plans for the near future without needing the notification to tell them to walk.

All other compartments can be adjusted to the right context: an input like a notification, call or nudge is processed via compartments like attitude, self-efficacy or motivation. This is then fed into a decision, together with availability variables like sitting in a meeting, illness, deadline and adherence such as being tired at the end of the day or having just engaged in walking. Potentially, other variables that also influence the decision can be added. The decision informs the binary physical activity that could include other categories on top such as a gym visit, taking a virtual class or going for a jog, which is then aggregated to feed back into the dynamical system, potentially at different time points as well. This generic structure is shown in figure 20.

Second, we have proposed a model to explain the separation of intervention and internalization, especially in the JITAI context. If the mechanisms and dynamics of an intervention are well-researched, future interventions can be improved. The simulation hinted that to some extent, the decreasing intervention

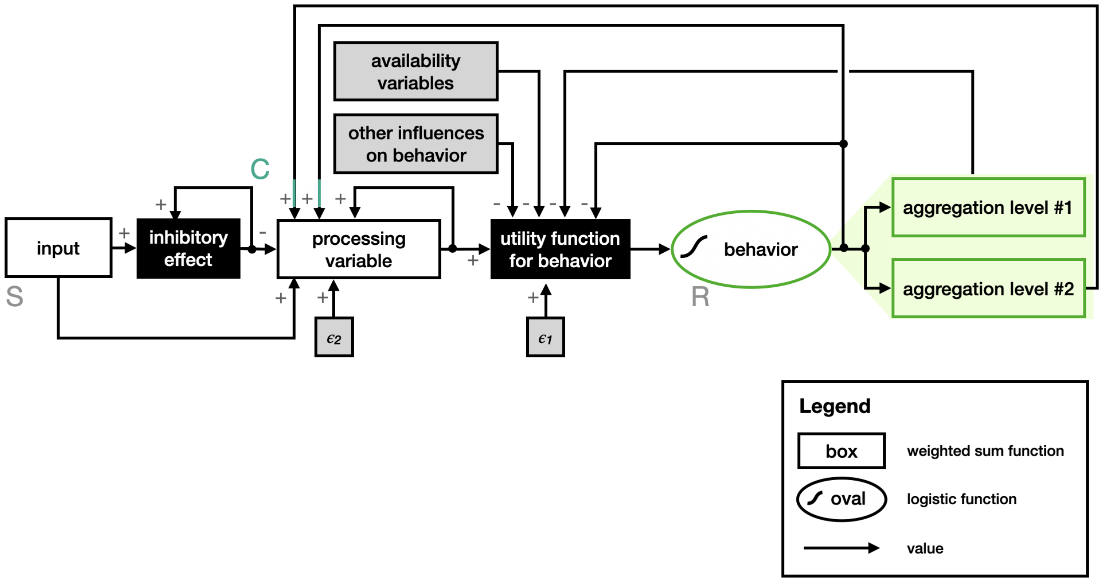


Figure 20: A generic model structure based on this SRC model.

effect could be a symptom of a low responsiveness after a notification. After a recovery period, a participant is likely to be responsive again. JITAIs largely emphasize the importance of timing, and responsiveness could add to the four stages of receptivity proposed by Choi (Choi et al., 2019). This time of low responsiveness could then be the cost of the intervention. Moreover, how long the positive effect of the stimulus lasts depends on the impact duration of the stimulus. To ensure that the intervention is internalized as much as possible, the notification delivery has to be tailored to a person's needs. Accordingly, along with availability and adherence, we propose responsiveness and the duration of the notification impact as measures to pick the ideal moment for a notification when a person is in the right state for it. Lastly, supposing that internalization indeed is due to a reinforcement mechanism indicates that interventions can explicitly support this feedback loop. As a general takeaway, this model emphasizes how the timing of a notification can be improved and by that ultimately contributes to sending better walking suggestions in JITAIs.

5.1 The model in context of past interventions

Setting this model into context, there have been heavy influences from fluid analogies from control systems engineering. Fluid analogies are a formalized framework from engineering to portray system behavior and recently, have been employed to assess the impact of digital health interventions (Riley et al., 2016; Conroy et al., 2019). The models are also set up in the JITAI context and estimate parameters idiosyncratically. One recent fluid analogy model uses Social Cognitive Theory (SCT) to describe walking interventions and could provide a framework to internalize skills and knowledge (Martin et al., 2020; Riley et al., 2016). Internalization could match the idea of self-efficacy and self-management skills building up, both compartments that are present in the SCT model.

Conveniently, a control system is usually initiated in a steady state and then receives inputs. In digital health interventions, these inputs correspond to notifications. This model follows their lead, treats notifications as inputs and derives the system's steady state as an initial simulation condition. Our model furthermore builds on their ideas for decisive diagrams with incorporated mathematical specifications. We also utilize their approach to simulate the dynamical system in different scenarios. By using existing model frameworks, they largely benefit from past methodological advances and clear definitions which this model builds on.

However, one of these key definitions indicates that all energy is conserved and all dynamics are treated as fluids that flow between compartments (Albertos and Mareels, 2010). This notion relies on linear relationships between compartments. This way, one is able to conduct certain analyses, *identify* the system and to generally profit from control system principles. In the case of the decision to walk we implemented, there is a flow from the utility U_t to walking W_t, but not for a decision against walking. If the threshold cannot be reached, the accumulation of t will not be saved for point $t+1$, but will be re-calculated for the next time step. Though past values influence the current time step, it is unlikely for the energy from utility to be conserved. Additionally, the value which is passed to the walking compartment W_t will be 0 or 1, not a continuous value that reflects by how far the threshold has been passed. This nonlinear bottleneck would therefore violate the key definition of energy conservation in fluid analogies. Though control systems are still able to model such a system, it may not be the most advantageous approach.

Another aspect is this system's heavy reliance on time aggregations. Previous control systems models have not explicitly included time aggregations in their system setup (Martin et al., 2020; Freigoun et al., 2017; Conroy et al., 2019), though different frequencies are essential in the later analysis of results. Control systems have also not used different frequency intervals of the notification (Conroy et al., 2019; Martin et al., 2020) which we strongly suggest likewise. We acknowledge that though not common, fluid analogies have the theoretical capacity to represent this model and decide against the full use of control systems out of simplicity. We choose a Bayesian statistical inference model with MCMC sampling in accordance with the binary decision bottleneck.

Among others, a different method to approach dynamical systems is dynamical networks which are increasingly used in psychopathology (Robinaugh et al., 2019; Haslbeck et al., 2019; Burger et al., 2020). Similar to control systems, they analyze complex systems by simulation first and derive consequence based on dynamics. Interestingly, recently, there has been an emphasis on slow and fast processes (Lunansky et al., 2020) and on different time intervals (Robinaugh et al., 2019). These studies considered a slow-changing rate parameter, which this model now also includes as β_9 in equation 4.5. In addition, the formulation of discrete-time equations was motivated and informed by the advances of a network model on panic disorder (Robinaugh et al., 2019).

In essence, the model as a whole builds on fluid analogies, it adopts the notion of inputs and steady states from control systems engineering, but adjusts it to a binary decision and to temporal differences. We therefore suggest future interventions to include both approaches, networks and fluid analogies, as valuable resources for specifying their models.

5.2 Propositions for future interventions

Focusing on coming interventions, we derive key suggestions from the simulated dynamics of this model.

Our goal is to answer key questions for an effective experimental design (Sheeran et al., 2017): what are strategies for promoting behavior change and under what circumstances? We recommend there need to be (i) sufficiently large recovery periods to allow responsiveness to rise again. (ii) Ideally, interventions are optimized to sending longer-impacting notifications that are also (iii) delivered just-in-time such that (iv) people build practice and engage in the behavior independently. As the implementation of the decreasing intervention effect was inspired by the physiological concept of habituation, interventionists can potentially follow research on habituation and correspondingly, apply it to a digital health intervention (Rankin et al., 2009). Nonetheless, the subtleties and differences between the two effects will need to be evaluated. Is the decrease stimulus-specific like habituation or will changing the medium not result in any new reaction? Then it will correspond more to a general sensory adaptation (Rankin et al., 2009; Groves and Thompson, 1970). Will the decreasing intervention effect show same rate sensitivity such that after a stimulus with a different frequency, the recovery period changes as well (Staddon, 2001)? Does the model need an additional cascade to model a decreasing stimulus impact even with sufficient recovery periods (Staddon, 2001)? Are there maybe additional factors such as annoyance that influence the decreasing reaction, too? On top of that, interventionists can decide which compartments are valuable to foster in their intervention of choice. What needs to be supported to promote internalization of knowledge, skills and practice? How could participants possibly build skills and internalize knowledge? We summarized possible suggestions for more meaningful notifications in future interventions in table 1.

Model features	Properties	Future interventions
Decreasing intervention effect	*Frequency of stimuli* (Staddon, 2001)	Send notifications at **different rates** to allow for recovery periods between stimuli.
	Spontaneous recovery (Rankin et al., 2009)	**Stop sending notifications** for a while to give a break if a person starts showing a decreasing response.
	Duration of stimulus impact	Send **thought-provoking notifications** or require the participant to interact with it. This way, the stimulus impact lasts longer until a person is responsive enough to receive a new notification and internalizes as much as possible.
	Stimulus specificity (Rankin et al., 2009)	Offer a **range of stimuli**: different notification tone or light, different app (eg. *iMessage* and *HeartSteps* app).
Internalization & reinforcement	Focus on the gain (Latimer et al., 2008; Tversky and Kahneman, 1992)	Choose to support both reinforcements from walking targeted towards the attitude towards walking. Write motivating messages that focus on the gain (**gain-framed message**) to support the reinforcement of walking.
	Immediate reinforcement (Skinner, 1953)	Choose to support the immediate reinforcement from walking. Send a notification *after* a person has walked to positively reinforce walking behavior.
	Different time aggregations	Support a variety of timescales: Give summaries and positive feedback of walking on a **weekly, daily and hourly level** This contributes to more relevant, timely feedback as suggested by health behavior motivation theories (Strecher et al., 1995; Nahum-Shani et al., 2018).

	Internalization of knowledge and skills	Shift the intervention design from supporting people to engage in the desired behavior to empowering people such that they build knowledge, skills and practice and engage in the behavior independently of the intervention (schraefel and Hekler, 2020).
The decision to walk	Notifications have to be tailored to reflect a) unavailability	Let participants **reflect on the barriers** that prevented them from walking in the daily EMA and support them in reducing these barriers. At the same time, adjust potential feedback to the users to be targeted towards the barriers, not to their attitude towards walking. Collect availability variables in broader **categories** (here internal and external barriers) and treat these potential barriers collectively.
	and b) capacity	Stop sending notification at the **end of the day** if a person has walked enough to not waste a notification.

Table 1: Suggestions for future interventions based on the SRC model features.

5.3 Outlook

This work aimed to understand digital health participants as a whole, describe their behavioral trajectories and by that allow for a separation of intervention and internalization. It operates at the intersection of statistical and mechanistic models, as it intends to work with existing data to analyze and articulate a dynamic hypothesis while it has also derived mechanisms from the literature and specified a-priori beliefs beforehand.

This model originated from a control systems-informed way of thinking, but has altered their approach. In that regard, it offers a new perspective, but needs to be evaluated with care. For the sake of simplicity, the model was limited to only include negative exogenous factors as availability. It cannot account for any positive external influence like social support, good weather or circumstances at work. In addition, the creation of the model was informed by the literature and by the *HeartSteps* data. As the sample size was rather small, the model could only be validated partially. Lastly, measuring psychological variables like attitude over time can potentially be tedious. Asking the right amount questions at the right times to both measure that variable and not annoy participants will be a challenge.

While offering a new perspective, the model includes new paths regarding collective variables, decision theory in digital health, time aggregations of slow and fast processes as well as the use of the operant learning SRC framework. Most importantly, it stresses the importance of how interventions can foster internalization of the knowledge, skills and behavior they are trying to convey. It sets a research agenda towards simpler models with fewer compartments that are still able to sufficiently explain dynamics in the data. On top of that, it challenges JITAI designers to incorporate the different stages of receptivity into the backbone of their models. Moreover, it shifts the focus of interventions from assessing a short-term effect towards re-thinking ways to support participants to build the knowledge, skills and practice needed to engage in that behavior. In addition, it raises questions for future interventions. Taken this model's structure, what additional compartments are necessary to properly describe walking interventions? Is the perception of the availability also important for the attitude towards walking? Is aligning the recovery period and the duration of the notification impact advisable? Or will it discourage participants because it becomes time-consuming and almost a burden? What are ideal moments to send walking suggestions? How does binary walking need to be operationalized for a digital health intervention to foster more walking? What are decisions in digital health influenced by? What do participants need to accumulate to internalize the intervention? Now is the time to start answering these questions with simple JITAIs in digital health.

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6 Appendix

The data

The simulation and validation is based on the *HeartSteps* data. A full ReadMe of the data and a documentation of the data cleaning process can be found at on GitHub (Gotzian, 2020).

Type	**Variable**	**Description**	**Available time points**
hectic	5-point Likert scale	rating: "How hectic was your day today?", asked every day	all-day EMA[1]
travel	binary	if a person traveled that day	all t in T
location.category	binary	location category ("work", "home" or the Google Place Type) based on the GPS coordinate, "home", "gym", "unknown", "work", or places starting with "rvpark", "park" or "campground" are counted as available, other places such as "bakery" or "store,point_of_interest,establishment", "grocery_or_supermarket" are counted as unavailable	EMA, suggestion, response[2]
recognized.activity	binary	Google Activity Recognition result; the detected activity type with the highest confidence level, evaluated within 90 seconds of time point, "still" and "unknown" are available, "augmented_vehicle", "in_vehicle", "on_foot" and "on_bicycle" are unavailable	EMA, suggestion, response
barrier.busy	binary	**barrier**: answer "No time/too busy" to barrier question[3]	all-day EMA
barrier.ill	binary	**barrier**: answer "Illness or injury" to barrier question	all-day EMA
barrier.sore	binary	**barrier**: answer "Sore muscles" to barrier question	all-day EMA
barrier.personal	binary	**barrier**: answer "Personal safety" to barrier question	all-day EMA
response	binary	evaluation of the suggestion by selecting "thumbs up" or "thumbs down", "thumbs up" is used as available, "thumbs down", "no_response" or "snoozed" is taken as unavailable	response

sleep	binary	assumed unavailability every day between 10pm and 6am (no actual sleep data)	all t in T

Table 2: Internal data used for $X1$.
[1] *all-day EMA*: response was given at daily EMA time, the value was extended for the entire day
[2] *EMA, suggestion, response*: at time of daily EMA, at time of suggestion and at time of response to suggestion via thumbs up/down
[3] *barrier question*: "Did any of the following make it difficult for you to be active today?"

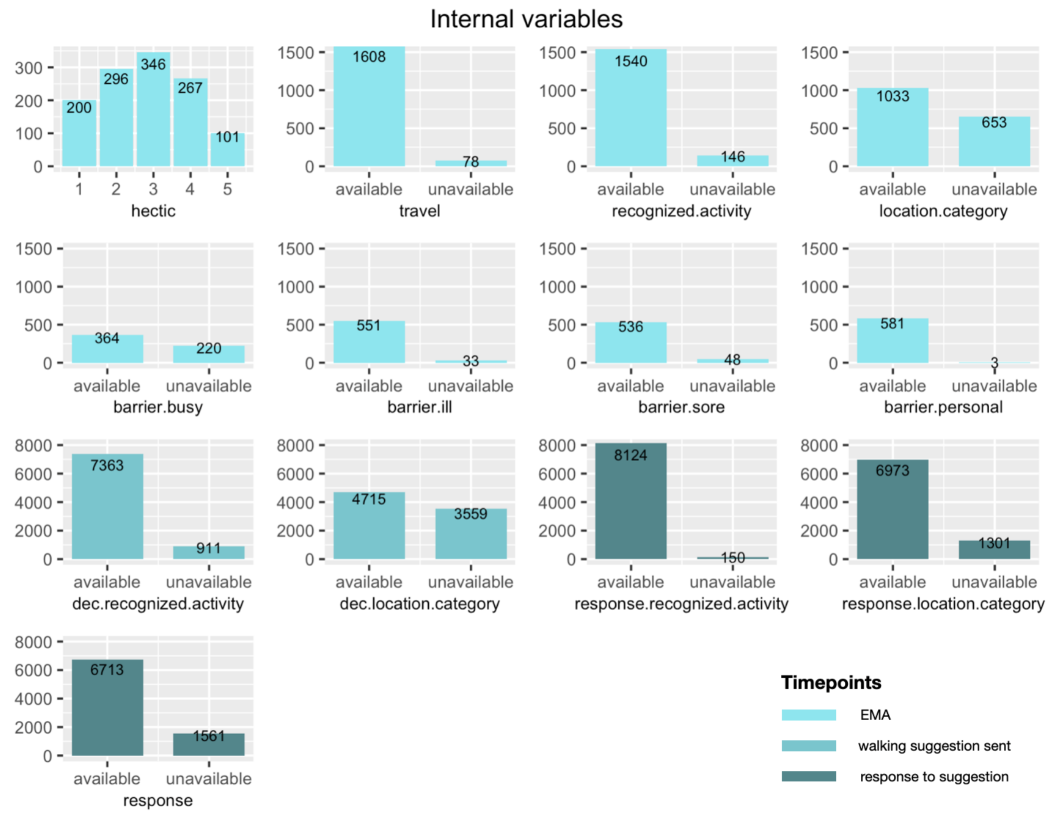

Figure 21: Distribution of variables used as internal barriers I_t. Data is available for three time points only, the completion of the EMA, when a walking suggestion is sent and when a participant responded to the suggestion.

Type	**Variable**	**Description**	**Available time points**
weather.condition	binary	**weather**: current weather condition classification from Weather Underground's API, based on the GPS coordinate, "ice pellets", "light freezing fog", any kind of rain or snow as well as "thunderstorm" is used as unavailable	EMA, suggestion, response
temperature	binary	**weather**: temperature in Celsius, based on the GPS coordinate. Temperature above 26°C is considered as critical according to German labor law (Arbeitsstättenrichtlinie A 3.5, 2010). Exposure to temperatures below -15°C can harm the respiratory tract, for untrained lungs, -5°C could already be harmful (Kennedy and Faulhaber, 2018). Temperatures of 27°C and higher as well as below -5°C are therefore set to unavailable.	EMA, suggestion, response
windspeed	binary	**weather**: windspeed based on the GPS coordinate. Windspeed above 40mph is considered a storm ("Deutscher Wetterdienst - Windwarnskala", 2020) and therefore used as unavailable.	EMA, suggestion, response
precipitation.chance	[0,1]	**weather**: precipitation chance (between 0 and 1) up to 60 minutes after time point, based on the GPS coordinate	EMA, suggestion, response
snow	binary	**weather**: if there is snowfall, based on the GPS coordinate	EMA, suggestion, response
barrier.weather	binary	**barrier**: answer "Poor weather" to barrier question	all-day EMA
barrier.place	binary	**barrier**: answer "No place to be active" to barrier question	all-day EMA
barrier.traffic	binary	**barrier**: answer "Traffic safety" to barrier question	all-day EMA
barrier.other	binary	**barrier**: answer "Other" to barrier question	all-day EMA

Table 3: External data used for $X2$.

Data	**Type**	**Variable**	**Description**	**Available time points**
$X3$	S_t	binary	if a notification has been sent at t	all t in T
target	W_t	binary	if a person walked $>$ 3 minutes or $>$ 500 steps at t	all t in T

Table 4: Data for notification delivery and walking.

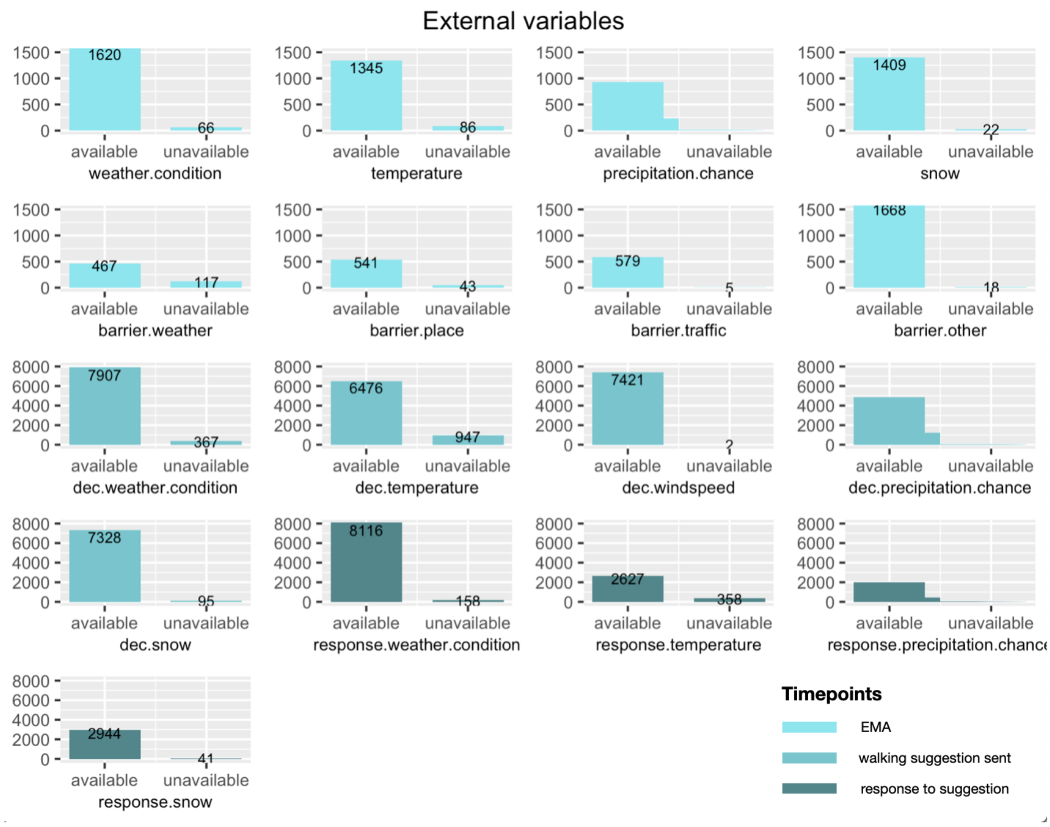

Figure 22: Distribution of variables used as external barriers E_t. Data is available for three time points only, the completion of the EMA, when a walking suggestion is sent and when a participant responded to the suggestion.

Figure 23: The prevalence of walking for each participant in the *HeartSteps* dataset. Across all individuals, it ranges from 5.7% for participant 34 to 32.7% for participant 4. On average, participants walked 18.4% of all time points ($SD = 6.3\%$). W_t=1 if a person walked > 3 minutes or > 500 steps at t.