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Multi-Stage Receptivity Model for Mobile Just-In-Time Health Intervention

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A critical aspect of mobile just-in-time (JIT) health intervention is proper delivery timing, which correlates with successfully promoting target behaviors. Despite extensive prior studies on interruptibility, however, our understanding of the receptivity of mobile JIT health intervention is limited. This work extends prior interruptibility models to capture the JIT intervention process by including multiple stages of conscious and subconscious decisions. We built *BeActive*, a mobile intervention system for preventing prolonged sedentary behaviors, and we collected users' responses to a given JIT support and relevant contextual factors and cognitive/physical states for three weeks. Using a multi-stage model, we systematically analyzed the responses to deepen our understanding of receptivity using a mixed methodology. Herein, we identify the key factors relevant to each stage outcome and show that the receptivity of JIT intervention is nuanced and context-dependent. We propose several practical design implications for mobile JIT health intervention and context-aware computing.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**;

Additional Key Words and Phrases: Just-in-time intervention, interruptibility, receptivity, prolonged sedentariness

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1 INTRODUCTION

The prevalence of smart devices and sensors allows us to use various intelligent positive computing services [42] which continuously monitor individual health conditions and unobtrusively infer surrounding contexts and internal states. This enables just-in-time (JIT) health intervention, which aims to provide the right type of support at the right time [53]. There has been a variety of studies on JIT health intervention aiming to resolve

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different health problems, including habitual smoking [55, 67], stress management for parents with attention deficit hyperactivity disorder children [61], eating disorders [63], and physical inactivity [8, 9, 18, 37, 45, 72].

To perform a target behavior elicited by JIT health intervention, people may be required to allocate a variety of efforts and resources. Thus, it is important to carefully consider when to deliver JIT health intervention [53]. A simple and widely-employed strategy is to deliver JIT support messages as soon as a user enters into a vulnerable state that could result in adverse health outcomes (e.g., long sedentary bouts, which contribute to type 2 diabetes and cardiovascular disease [7]). However, if the support is given at an inappropriate moment, this strategy may disrupt users' ongoing tasks and negatively influence adherence. In some cases, it may even cause safety risks, such as by distracting users from driving.

Fortunately, problems with delivery timing of JIT support can be alleviated if we know when people are most likely to engage in the target behaviors suggested by JIT support, namely, when people are in a highly *interruptible* state. A simple heuristic method is to create fixed rules for unavailable situations (e.g., not asking users to stand up while driving) [36]. More elaborate approaches include leveraging Ubicomp literature on automatic detection of interruptible moments. Prior studies showed that *interruptibility for message delivery* depended on message content and perceived disruption levels [50], places characteristics [48], types of ongoing tasks [13, 48], and personality traits [78]. Although the target behaviors suggested by JIT support typically demands higher workload than message checking, interruptibility literature clearly indicates that receptivity of JIT intervention varies widely across a variety of contextual factors, contents, and individual characteristics.

In this work, we aim to deepen the understanding of receptivity for mobile JIT health intervention by leveraging an interruptibility model (i.e., Decision-on-Information-Gain (DOIG) [74, 75]), which describes multiple stages of sequential decisions in response to a given notification. We extend this model to capture the JIT intervention process comprising multiple decision stages: perception of the intervention signal; assessment of availability; determination of adherence; and actual performance of a target behavior. Note that health behavior promotion is a complex process, and there are a variety of determinants (e.g., contexts, motivations, and health beliefs) related to its success. Thus, we limit our scope to well-known contextual and psycho-physiological factors to later allow researchers and practitioners to use context-aware computing to infer the receptivity of JIT intervention.

Towards this goal, we focus on health interventions designed to prevent prolonged sedentary behaviors. We build a prototype service, *BeActive*, that delivers timely suggestions for active breaks (e.g., "stand up and move around for a minute") via users' smartphones and watches whenever uninterrupted sedentary bouts (e.g., 1-hour sitting) are detected. For each suggestion, we ask the user to report the context (e.g., location, social setting, and ongoing tasks); cognitive/physical state (e.g., level of focus and physical fatigue), and their decision on intervention (e.g., perception, availability, adherence, performed behaviors). We conducted a 3-week field study with 31 participants and collected 5,409 self-reports. By analyzing these reports with multilevel logistic regression, we identified key predictors relevant to users' response behaviors at each stage.

Our results show that the receptivity of JIT intervention is multifaceted and context-dependent. The focus on ongoing tasks negatively contributes to all stages, and physical fatigue is a major contributor affecting adherence. Despite the negative effects of social setting on perception and availability, less important social engagements such casual conversations tend to positively transition to active breaks. Based on these findings, we propose several design implications, such as delineations of availability and adherence, contextualized guideline support, and automatic receptivity inferencing.

2 RELATED WORK

2.1 JIT Health Intervention

Advances in sensor and networking technologies allow us to unobtrusively monitor individual states and surrounding contexts in real-time, while proactively providing cues and information about users. Such advances allow to provide the right type of support at the right time, JIT health intervention [53]. Previous work has employed JIT intervention to deal with a variety of health-related issues, including smoking cessation [55, 67], prevention of eating disorders [63], reducing physical inactivity [8, 9, 18, 37, 45, 72], and stress management [61].

An essential element for JIT health intervention success is the determination of when a support message should be delivered to a user. Typically, the right time of support delivery is regarded as the time at which users are vulnerable to adverse health conditions. In the case of smoking cessation, interventions are triggered when smokers visit a place where they have frequently smoked [55] or when they experience high stresses over a short period [67]. To decrease sedentary behavior, opportune timing requires prompts to be delivered when prolonged inactivity is detected (e.g., step count is less than a certain threshold) [8, 9, 45, 72].

An additional consideration for intervention delivery timing is finding when a user is *receptive* to a given JIT support [52]. Receptivity of JIT support is defined as the conditions that a user can receive, processes, and adhere to the support provided [52]. JIT support requires users' perceptual, cognitive, and motor resources and may even be considered *disruptive* to ongoing tasks. Thus, JIT support has similar characteristics to interruption. In the field of ubiquitous computing, researchers actively striven to understand, define, and detect *opportune moments* for interruption. Understanding interruptibility will help us better estimate receptivity of JIT support. Prior studies proposed various measures of defining interruptibility for an incoming task, including subjective sentiment [50, 58, 78] and/or reaction latency/presence [4, 13, 22, 48–50, 58, 68, 74, 75]. In the vehicular contexts, researchers also considered safety and task performance aspects due to dual-tasking nature of interruption [34]. Furthermore, recent studies focused on *adherence to incoming interruptions*. For example, actual interaction with incoming content (e.g., tapping on notifications) can be regarded as evidence that a user is in a receptive state [48, 50, 74, 75]. Receptivity may additionally consider the engagement of the non-primary content [59].

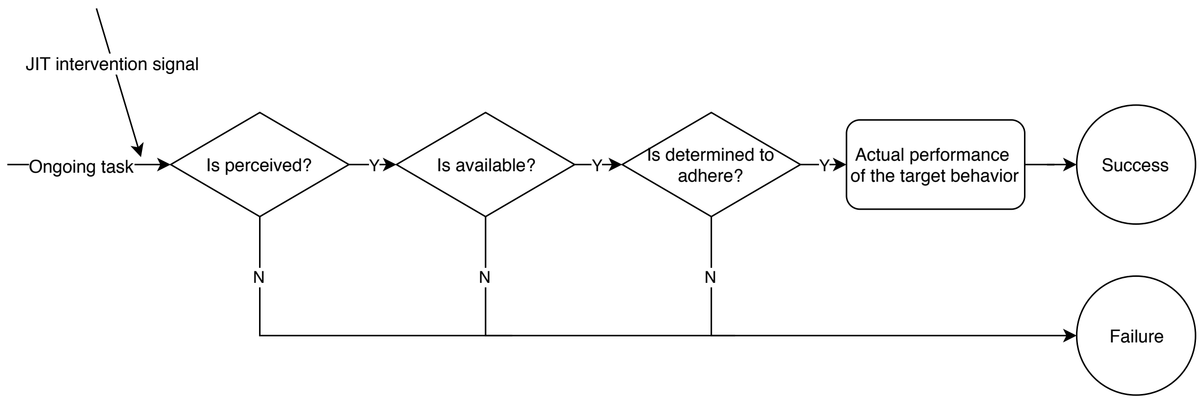
Apart from delivery timing, JIT support messages should be carefully tailored for targeted health outcomes, users' internal states, and surrounding contexts, because message contents can have a strong influence on a user's receptivity to given support [23] and on health outcomes [37]. Recent studies proposed a more advanced concept of JIT intervention, JIT adaptive intervention, where the content and timing of JIT intervention was tailored per individual characteristics and contexts [52, 53]. These studies highlighted that receptivity was indeed a complex and multifaceted process. Furthermore, it demanded we further study receptivity.

Referencing a variety of issues about JIT intervention, this work explores users' receptivity to given JIT health support across diverse contexts. Our work builds upon previous interruptibility studies that focused primarily on the receptivity of a relatively simple task with minimal workload (e.g., unlocking/touching the smartphone). Our work aims to deepen the understanding on the receptivity of JIT support, which often requires users to perform a more effortful and time-consuming task (i.e., standing up and moving around for a period). Unlike interactions with the smartphone, this task might be differently received by users because of its unique characteristics, including the definite suspension of ongoing tasks and the requirement of physical effort. Whereas this task is common to health intervention techniques for reducing physical inactivity and sedentariness, there is still a lack of understanding about how users perceive and react to the intervention messages in situ and what contextual factors are related different stages of *human information processing and behavior controlling*.

2.2 Technological Intervention for Inactivity and Sedentariness

Researchers have studied a variety of technological interventions to promote physical activities. One widely employed intervention is to promote self-reflection on individual health behaviors by measuring health-related indicators (e.g., calories, step counts, time to engage physical activities) using a variety of sensors. For example, commercial fitness trackers (e.g., Fitbit) monitor and visualize users' health-related metrics, including step counts and calorie expenditures. Additionally, there have been several studies that enhanced the self-reflection of physical activity via aesthetic symbols displayed on a mobile device [17], interactions with a reflection companion [38], and

Fig. 1. Decision stages in JIT intervention stage model



an ambient light display [25]. Social support also has been a frequently used technique for health intervention, including sharing step counts with friends or an online community [16, 26]. Furthermore, there has been a variety of studies promoting physical activity, including making activities fun by designing exertion-based games [10, 14, 15, 51], personalized suggestions of physical activities/food using multi-armed bandit [62], inconvenient gadgets requiring users to perform physical activities for operation [64], and slowly moving robots for unobtrusive posture correction [69].

With the promotion of physical activities, there has been increased attention on the intervention of sedentary lifestyles, which are known to causes a variety of chronic diseases, metabolic dysfunction [56, 77] and hospital readmission [5]. Even for people who engage in a sufficient amount of physical activities, uninterrupted sedentary bouts still contribute to overweight and obesity [71]. Thus, increases in breaks from sedentary time are beneficial to reduce waist circumference, independent of the time to engage in moderate-to-vigorous physical activities [28]. To interrupt prolonged sedentariness, studies have often attempted to deliver prompts, including notifying of prolonged sedentary bouts [45, 76], alerting prolonged sedentariness with a traffic-right symbol [27], and suggesting short-bouts of physical activities (e.g., walking, sit-ups, squats) [8, 9, 57, 72]. Additionally, active workstations, which enable workers to perform office tasks while engaging in a variety of physical activities, has contributed to reducing sedentary time [3, 6, 12, 32].

Because occupational sitting comprises a large proportion of daily sedentary time and is often prolonged [47, 73], sedentary interventions typically consider only the work environment. As with conventional smartwatches and their wearing patterns [31], we aim to intervene in prolonged sedentary behaviors occurring not only during working hours but also at leisure times. Leisure-time sedentary behavior was also revealed to contribute to obesity in adults [71]. Thus, it is meaningful to consider sedentary interventions during non-working hours. Understanding a variety of contextual factors relevant to receptivity of the JIT support is critical for building context-sensing systems that can better deliver JIT support messages.

3 JIT INTERVENTION STAGE MODEL

We propose a JIT intervention stage model that unifies the entire process from intervention message arrivals to the actual execution of suggested health behaviors. Our model comprises four stages: perception of the intervention signal; assessment of availability; determination of adherence; and actual performance (see Fig. 1). This model applies to a range of JIT interventions that deliver timely in situ support as a form of external stimuli to draw attention, require timely reaction to a given support message, and demand effort and time to complete a recommended behavior. For example, Fitbits provide JIT support to achieve a certain level of physical activities (e.g., more than 250 steps every hour). When detecting the lack of physical activities in the hour, the Fitbit sends vibrotactile and visual cues to inform users of their insufficient physical activities, suggesting further physical activity. If users perceive these cues, they must then decide decide whether to follow the suggestion before another hour passes. If suggestions are accepted, users then spend physical effort and time to achieve the suggested goal.

3.1 Stage 1: Perception of the Signal

The first stage, perception of the signal (or support message), assesses whether a user perceives external stimuli triggered by the JIT intervention. The signal is delivered via different sensory channels and modailites. For example, users can commonly receive notifications on a smartphone [8, 37, 60, 61, 72, 76]. A pop-up dialogue on the desktop computer [9, 27, 45] or ambient display [29, 33] are also feasible. Previous works proposed a variable similar to signal perception, such as the *seen time* of incoming messages or notifications, which can be measured by tracking device events (e.g., unlocking a smartphone, turning the screen on) [13, 50]. However, perception here implies the concept of interruption detection [39]. An undetected interruption is denoted as oblivious dismissal. These are very different from the seen time. Perception is an automatic process of human beings that has nothing to do with an intent to dismiss or follow a signal [40]. However, seen time is a mixture of perception and decision making and is affected by users' (mis)interpretation of or intention to dismiss (or consume) incoming signals. For example, users might ignore a signal when they are too busy or do not want to handle it immediately [13], which leads to a longer seen time.

3.2 Stage 2: Assessment of Availability

After perceiving the signal, users read or interpret the JIT support message provided. For the given context, they then assess whether they are available to perform the target behavior. A previous study defined availability as an individual's capacity to engage in incoming and unplanned activities [68]. An available state indicates that users can respond/react to incoming information without significant disruptions [30] or within a certain amount of time after the signal is delivered [68]. These definitions embody a variety of elements used to determine an individual's available state, such as motivational factors, contextual factors, social norms, and characteristics of target behavior. To simplify our modeling, we omit motivational factors from this stage, but we incorporate them in the next stage. Thus, we re-define availability for JIT intervention 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.*

3.3 Stage 3: Determination of Adherence

When users are triggered to perform a target behavior suggested by the JIT support, they must decide whether to actually perform the target behavior. This is adherence. The decisions of this stage are influenced by health beliefs, motivations, and individual states. For example, users may intentionally dismiss incoming JIT support messages, because suggested behaviors are less significant than their ongoing tasks [39], or they feel physically too tired to perform the suggested behaviors [45]. Lack of motivation for behavioral change causes users to reject the support provided if the target behavior is relatively complicated [24]. Additionally, adherence is unlikely to occur if users believe that the support is not beneficial enough or that they are not vulnerable to the health risks [65]. Thus, there are a variety of potential factors contributing to adherence, and our model can be extended to include sub-decision stages accounting for these factors, which will be a future work.

3.4 Stage 4: Actual Performance

If users decide to adhere to the JIT support message, they should suspend their ongoing tasks and switch to the target behavior suggested. When completing the target behavior, users are expected to resume their ongoing tasks. Our model includes the method used to actually perform their target behaviors, because it is important to investigate actual adherence. For example, users may perform different activities than suggested, or they may under- or over-perform. In reality, different interventions may stipulate different adherence levels. In the case of encouraging physical activities, for example, people tended to engage in walking longer than the suggested amount of time once they started [72]. For tailoring JIT interventions to enhance intended health outcomes, it is important to understand how individuals actually performs the target behavior for a given support.

3.5 Discussion

The JIT intervention stage model that we propose builds upon the DOIG-based interruptibility model, which is focused on the consumption of mobile-phone notifications [74, 75]. The DOIG-based model breaks down a user's response into a sequence of micro-decisions based on the user's interactions with the device. Potential micro-decisions for this model include the reachability stage: whether a user will at least react to an incoming notification, or will not react at all, leading to a null response; the engage-ability stage: (when perceived) whether the user will begin to respond, but will discontinue consuming the interruption, leading to a partial response if discontinued; and the receptivity stage: (when the user decides to continue the consumption) whether the user will be receptive to completing the requested responses, leading to a complete response if receptive.

While the DOIG-based interruptibility model was originally created to explain the key decision stages of content consumption for a given notification, it can also partly explain JIT intervention scenarios. Suppose that JIT support messages are delivered in the form of mobile notifications, including vibrotactile feedback for smartwatches. After perceiving a JIT support message during the reachability stage, users may successfully consume the message during the engage-ability and receptivity stages. However, the DOIG-based interruptibility model mainly focuses on the observed response behaviors resulting from interactions with mobile notifications. Thus, whereas perception (or reachability) is common in both models, the other two stages in the DOIG-based model do not clearly capture the detailed decision factors related to performing the target behavior as prescribed in the JIT support message.

Beyond mobile notification delivery, our JIT intervention stage model details the latent decision factors for *executing target behaviors* in relation to Fogg's Behavior Model (FBM) [24], which proposes three constructs for behavioral change: motivation, simplicity, and triggers. JIT intervention often requires users to perform prescribed target behaviors that can be time-consuming, effortful, and even socially-deviant to some extent under certain situations. To lead users to actually execute the target behaviors, users should believe that they will be available to perform the target behavior at the time the JIT support message arrives. This points to the availability assessment stage in our model, which corresponds to the simplicity aspect of FBM. In addition, users should get motivated enough to perform the target behaviors. The adherence stage in our model is closely related to the motivation construct in FBM. Likewise, the adherence stage in our model is closely related to the motivation construct in FBM.

4 CASE FOR PROLONGED SEDENTARY BEHAVIOR INTERVENTION

We elaborate research questions related to users' receptivity to a given JIT support using the proposed intervention stage model. As stated, there are a variety of potential factors contributing to each stage, including contexts, motivational factors, personality traits, and suggestion contents. In this work, we primarily focus on contextual factors and physical/cognitive states, because the ultimate goal is to facilitate automatic detection of the receptivity in the JIT support with contextual and physiological sensing based on ubiquitous computing technologies. Understanding the effects of motivation and belief factors is a part of our future work.

Among a variety of health concerns, we focus on prolonged sedentariness. There are several reasons for choosing sedentary intervention. Uninterrupted sedentary behavior is prevalent nowadays and is known as the cause for a variety of chronic diseases and early mortality [7]. There have been many attempts and practices of sedentary intervention, and prolonged sedentariness is relatively simple to measure using mobile sensors.

Our intervention scenario prompts users with intervention messages via smart devices, similar to prior studies [8, 76]. In our scenario, the smartphone continuously monitors a user's sedentary behavior. When detecting a prolonged sedentariness (e.g., uninterrupted sedentary behavior exceeding a predefined duration), the smartphone delivers a notification that suggests the user to stand up and move around for a minute. This is called an *active break*. With our proposed JIT intervention stage model, this scenario can be separated into conscious or subconscious decision stages.

When the intervention service detects prolonged sedentariness, the smartphone notification is delivered to stimulate users' sensory organs (via the current smartphone ringer mode) and draw their attention to the arrival of the JIT support message. Users then subconsciously perceive or miss the notification. This is the first stage, the perception of a signal. Success in this stage results from different factors across types of ongoing tasks, social settings, locations, and/or physical/cognitive states. Our first research question is as follows:

> *RQ1. What are the contextual factors and physical/cognitive states that are relevant to the perception of the signal?*

If users successfully perceive the signal, they then check the suggestion contained in the notification. As stated earlier, our activity suggestion is to stand up and move around for a minute. Users must judge whether they are available to comply with the suggestion. For example, we can assume that users are unlikely to be available to stand up and move around while driving or during a wedding. Additionally, users' physical conditions can negatively influence on availability. To understand such potential factors affecting availability, the second research question is formulated as follows:

> *RQ2. What are the contextual factors and physical/cognitive states that are relevant to the perceived availability of active breaks?*

When users perceive the intervention signal and think about standing up and moving around, they decide whether they will voluntarily break their sedentary behavior, suspend their ongoing task (if any), and adhere to an active break routine. This series of activities is effortful and time-consuming (and sometimes burdensome). Thus, some users do not want to engage, even though they are available. To reveal the factors that influence adherence of the active break, our third research question is formulated as follows:

> *RQ3. What are the contextual factors and physical/cognitive states that are relevant to the adherence of active breaks?*

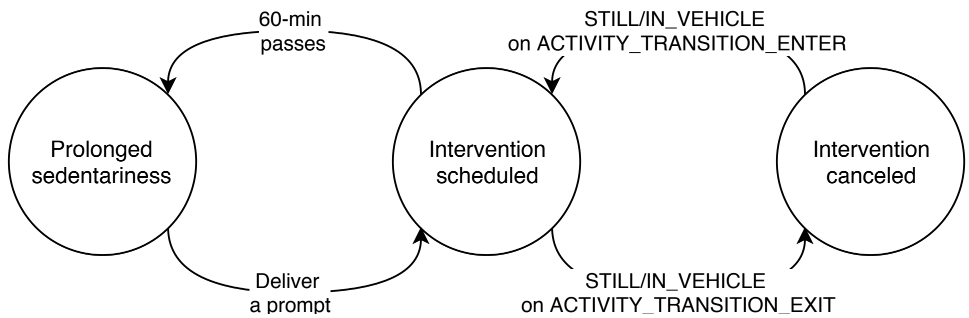
Finally, if users make positive decisions in all previous stages, we assume they actually stand up and move around. This suggestion provides some degrees of freedom to choose types of activities for a session. For example, users might engage in short bouts of obvious physical activities, such as stretching or walking. However, they might also go for a walk for refreshment and relaxation with no specific intention to increase in their physical activity. To explore how users actually perform during a session of active breaks, the final question is as follows:

> *RQ4. What are the types of activities during an active break session?*

5 STUDY PROCEDURE

To answer our research questions, we implemented a research prototype of sedentary intervention, *BeActive*, which provides timely support to break prolonged sedentariness and allows users to report different decisions

Fig. 2. State diagram of BeActive's JIT intervention process



about given support and relevant factors to such decisions. In this section, we begin by presenting how BeActive works and which types of questions were included for the self-report. We then elaborate on our field trial that lasted 3 weeks.

5.1 Implementation of BeActive

Our research prototype of sedentary intervention, BeActive, is comprised of three major components, sedentary behavior sensing; intervention prompt delivery; and self-reporting on surrounding contexts, cognitive/physical states, and decisions to a given JIT support message. BeActive is operated on the Android mobile phone whose operating system version is equal to or higher than 6.0.0 (Marshmallow). During an implementation period, we employed iterative design process to identify usability and functional issues. We conducted several pilot tests, including two rounds of low-fidelity prototype tests with three and four participants, and a high-fidelity prototype field test with seven participants for three days. All prototype tests were conducted with students on our campus.

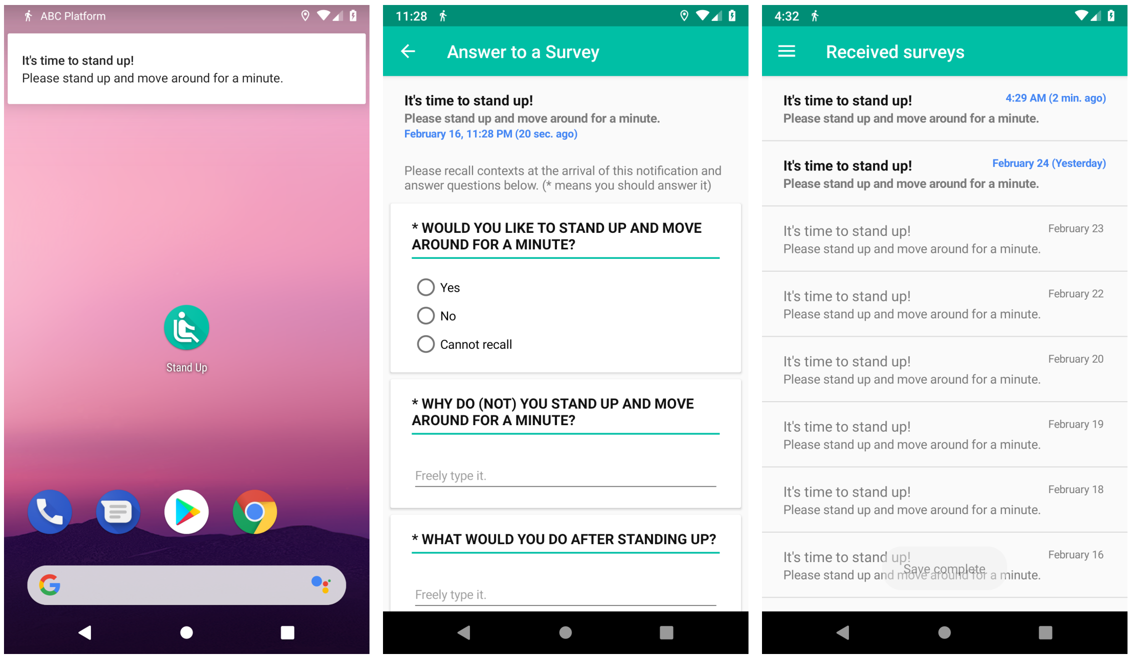
5.1.1 Sedentary Behavior Sensing. BeActive continuously monitors a user's mobility status using Google's Activity Recognition Transition API[1] on a smartphone. This API allows applications to subscribe to activity transition events, such as entering into (*ACTIVITY_TRANSITION_ENTER*) or exiting from (*ACTIVITY_TRANSITION_EXIT*) activities of interest. Supported activities are *IN_VEHICLE* (i.e., the device is in a vehicle), *RUNNING* (i.e., the device is on a user who is running), *WALKING* (i.e., the device is on a user who is walking), *ON_FOOT* (i.e., WALKING or RUNNING), *ON_BICYCLE* (i.e., the device is on a bicycle), and *STILL* (i.e., the device is not moving).

To detect a user's sedentary behavior, we consider two activities, such as STILL and IN_VEHICLE, because both activities accompany prolonged sedentariness. When a user's device becomes stable (e.g., sitting down or leaving the device on a desk) or begins to travel by car, the API reports STILL/IN_VEHICLE on ACTIVITY_TRANSITION_ENTER, otherwise it reports STILL/IN_VEHICLE on ACTIVITY_TRANSITION_EXIT. When entering these activities, our service schedules the intervention prompt to be delivered after 60-min that is reported as preferred work duration [45]. When the API reports exiting these activities, our service cancels the scheduled prompt, if any (see Fig. 2).

5.1.2 Intervention Prompt Delivery. When a user's devices remain stable with no mobility changes after an intervention prompt has been scheduled, the intervention prompts appear on a user's smartphone in the form of a push notification, which includes the suggestion of an active break, as shown in Fig. 4a. The sensory channels

[1] https://developer.android.com/guide/topics/location/transitions.html

Fig. 3. Overview of BeActive



(a) Active break suggestion via notifications

(b) Self-reports

(c) A list of prompts delivered. Unanswered ones is highlighted in bold.

for intervention delivery correspond to a user's current setting of the ringer mode. When the prompt is triggered, the service re-schedules the next one in 1 hour.

Considering the characteristic of timely support for JIT intervention, we presume that a user's decision on given support should be made within a short duration from the moment of support arrival. However, users' receptivity depends on the current ringer mode. Recent studies have shown that the seen time of the notification is longer when the ringer mode is set to silent, compared to other modes [50]. Additionally, people typically set their ringer mode to silent or vibrate during working hours and sleep [13], as did our participants in the pilot test. Because the intervention prompts are also delivered in the form of notifications, the ringer mode can have a significant influence on the receptivity of the prompts. To mitigate delayed or missing cacused by the ringer mode, we also used a wrist-worn smartwatch to deliver vibrotactile feedback independent of the smartphone's ringer mode.

5.1.3 Self-Reporting on Contexts, Cognitive/Physical States, and Response to JIT Support. To capture users' contexts and decisions on a given JIT support message, we provided questionnaires and instructed respondents answer it by clicking notifications. Given that users could miss the notifications or defer their responses, we allowed them to view the list of all prompts (and associated questionnaires) and to answer any missed questions later (see Fig. 4c). As shown in Table 1, we first asked whether users took an active break after receiving the prompt. We then asked them to detail the reasons for their decision and their resulting movement behaviors. We asked them to choose the perception status of the notification, and their availability for an active break. Furthermore, we asked

Table 1. Questionnaire items to capture contexts, cognitive/physical states, and decision on a given JIT support message.

Question	Answer type
Would you like to stand up and move around for a minute?	Yes / No / Cannot recall
Why do you (not) stand up and move around for a minute?	Free text
What would you do after standing up?	Free text
Did you perceive the arrival of this notification?	Yes / No / Cannot recall
Are you available to stand up and move?	Yes / No / Cannot recall
Please describe your context as follows:	
- Where are you?	Free text
- Whom are you with?	Free text
- What are you doing?	Free text
Please rate your level of focus on your ongoing task	in 7-point Likert scale
Please rate your level of fatigue	in 7-point Likert scale

of their situational context (i.e., place, social setting, and ongoing task) and of their cognitive/physical status (i.e., level of focus/fatigue on a 7-point Likert scale). For measuring fatigue, we used the Samn-Perelli fatigue scale (e.g., 1: fully alert, wide awake; 3: okay, somewhat fresh; 5: moderately tired, let down; and 7: completely exhausted, unable to function effectively) [66].

For accurately capturing contexts and states, at the beginning of the questionnaire, we displayed the arrival time of a given prompt, and when answering the questions, users were explicitly asked to consider their situation at the time of message arrival or up to 5-min afterwards. For example, if a user could perceive the arrival of an intervention prompt during this 5-min period, the message was marked as perceived. The threshold of 5-min was derived from findings of people seeing notifications within approximately 5-min, except for when the ringer mode is set to silent [50]. We carefully considered the wording of the self-report questions (particularly about the tense) regarding whether a user takes an active break and what they do during the break. This is because users could answer these questions right after the prompt arrival, during/after the active break, or even after several hours. We initially tried to vary the tense of each question based on contexts, but during the pilot trials, our participants complained that tense variations were confusing. For this reason, we used the present tense (as shown in Table 1) and explicitly instructed users to answer the questions based on what they had done, or what they will definitely do within the 5-min period after message arrival. After 5-min of notification, we simply assumed that a participant did not perceive the notification in time or intentionally dismissed it. Then, all questions were changed to the past tense so that participants could recall the contexts of their notification times. The responses were stored in a user's smartphone and uploaded to the server via a Wi-Fi network.

5.2 Field Study

For the field study, we recruited 31 participants (14 females; age: M=29.00, SD = 7.03) from an online campus community, faculty mailing list, and Facebook in October 2018. They were required to have spent at least 6 hours sitting per day. Their occupations varied, including nine graduates, seven undergraduates, nine office workers, five IT developers, and one plastic surgeon. In an introductory session, we instructed the participants on using the service and asked them to use it for 3 weeks. To explore a variety of contexts including working hours and leisure time, BeActive was set to track prolonged sedentary behavior (i.e., 1-hour sitting) from 8:00 to 23:59 so that the participants could receive the prompts from 9:00 to 23:59 every day during the study. Thus, participants received at most 15 prompts per day if they never moved between 8:00 to 23:59. Additionally, we asked participants to note any erroneously-triggered prompts after having moved during the past hour. This could result from sensing errors or moving without holding the phone. We excluded those prompts from our analysis.

We also distributed smartwatches, Fitbit Ionic, to help participants perceive the arrival of intervention prompts. Thus, notifications were delivered via both smartphones and smartwatches. We configured the Fitbit Ionic to deliver feedback triggered by only our service to reduce confusion. Any health-related functions that the Fitbit Ionic supports by default (including showing physiological stats on the display and hourly activity suggestion) were deactivated to prevent potential influences on users' behavior.

After the 3-week field study, we conducted in-depth exit-interviews for approximately 1 hour per participant to explore user experiences. Our interview mainly focused on general tendencies to the reactions to given JIT support messages and activities performed during active breaks. All interview sessions were recorded and transcribed for thematic analysis. Each participant was compensated with 145 USD, and no additional incentive for adhering to the active breaks was given.

6 DATA ANALYSIS

In this section, we present how we analyzed self-reports and interviews from the three-week field study. We first elaborate on the exclusion criteria of responses. Then, we describe strategies to label each response, considering contextual factors and physical activities performed during active breaks. Using these labeled responses, a regression analysis was performed to understand how a user's contexts and cognitive/physical states related to different decision stages (i.e., perception, availability, and adherence) of the JIT intervention model we proposed. Additionally, we qualitatively analyzed interview and self-report responses to find reasons for the decisions made in response to a given support message (i.e., "Why do you (not) stand up and move around for a minute?") to corroborate our findings from the regression analysis.

6.1 Exclusion Criteria of Context Self-Reports

During the field study, a total of 5,409 prompts were delivered to 31 participants. We provided a list of received prompts (see Fig. 4c) so that participants could answer any missed or non-responded questionnaires later. Thus, participants completed all 5,409 questionnaires. However, we found that seven participants completed their questionnaires quite late (i.e., more than 20% of their responses were answered after 24 hours) and four did not even wear the Fitbit Ionic on a regular basis. Therefore, we excluded 1,337 responses from those seven participants (P25 to P31). We only considered the remaining responses (n=4.072) from the 24 participants (age: M=30.88, SD=6.73) for data analysis. We then removed 909 invalid responses, such as those responding that they took active break but were unavailable to do anything active, those providing inaccurate answers to the question items (e.g., "Where are you?": "Sleeping"), and those answered to erroneously triggered prompts (i.e., prompts delivered although participants already have moved in the last hour or were currently moving). The following analysis was conducted with remaining 3,163 valid responses.

6.2 Labeling Responses

From the self-report responses, we categorized the contextual information (i.e., where they were located and what they did, including the social setting). For this, two authors manually examined responses using an affinity diagram to iteratively develop a coding scheme for categorizing contextual factors and activities performed during the active break until consensus was reached. Final themes derived are described in Table 2.

Table 2. Categorization criteria

Category	Definition	Examples from self-report
Location		
Home	Primary living spaces used as a permanent residence for an individual	Home, dormitory, living room
Work	Primary places of employment (for employees) or education (for students)	Office, meeting room, laboratory
Restaurant/Cafe	Places where meals/drinks are prepared and served	Restaurant, cafe, bar
Vehicle	Vehicles with wheels and an engine, used for transporting people	Car, taxi, bus, train
Miscellaneous	All other locations	A movie theater, barbershop, hotel
Social setting		
Social	Co-located and engaging in an activity with someone	Talking with friends, getting a haircut, taking a class
Asocial	Staying alone or co-located, but no social interaction with someone	Watching TV alone, sitting on a bus
Ongoing task		
Working/Studying	Doing something related to a job (for employees) or studying (for students) by themselves	Doing office work, programming, homework
Sleeping	The state of being asleep	Sleeping in a bed, taking a nap
Resting/Relaxing	Resting for a period of time to relax and refresh	Chilling in bed, lying in a bed, doing something on the phone
Video watching	Watching videos	Watching YouTube, watching TV
Class/Meeting	Group work for a study or job	Having a meeting, taking a class
Eating	Eating some food or meal	Having lunch, Dining out
Gaming	Playing a video game on a computer or a smartphone	Playing League of Legends, playing a mobile game
Conversing	Having a face-to-face conversation with someone	Chatting with a family, talking with a friend
Getting ready for bed	The state of preparing for sleep in a bed	Getting ready for bed
Calling/Texting	Having an online conversation with someone	Making a phone call, online chatting
Right after waking up	The state of having just awakened from sleeping but still being in bed	Just opened up eyes in a bed, woke up in a bed
Driving	Driving a vehicle	Driving a car
Miscellaneous	All other activities	Getting a haircut, getting an endoscopy

Table 3 shows the distribution of responses across categorized contexts and decisions on our JIT support. For location, we used four major categories: *home*, *work*, *restaurant/cafe*, and *vehicle*. The social setting was divided into *social* and *asocial*, depending on the likelihood of possible social interaction. An asocial setting is one where either a participant is alone or with other people where social interaction is less likely to happen (e.g., public transportation). In contrast, a social setting is one where either a participant is co-located with other familiar people (e.g., friends and families) or engages in activities together with others.

Table 3. Distribution of the responses across different locations, social settings, and ongoing tasks

	Total (n=3,163)	Perception		Availability (Perception=Yes)		Adherence (Per./Avail.=Yes)	
		No	Yes	No	Yes	No	Yes
Location							
Home	1,594	748	846	91	755	465	290
Work	1,240	261	979	206	773	510	263
Restaurant/Cafe	181	47	134	35	99	69	30
Vehicle	48	19	29	26	3	2	1
Miscellaneous	100	37	63	36	27	22	5
Social setting							
Social	1,768	573	1,195	81	775	503	272
Asocial	1,395	539	856	313	882	565	317
Ongoing task							
Working/Studying	1,216	222	994	83	911	602	309
Sleeping	564	564	-	-	-	-	-
Resting/Relaxing	360	58	302	19	283	173	110
Video watching	272	37	235	27	208	122	86
Class/Meeting	198	57	141	120	21	19	2
Eating	171	68	103	39	64	43	21
Gaming	102	40	60	14	46	37	9
Conversing	96	25	71	30	41	18	23
Getting ready for bed	55	6	49	15	34	33	1
Calling/Texting	38	7	31	15	16	10	6
Right after waking up	30	7	23	1	22	4	18
Driving	29	11	18	18	-	-	-
Miscellaneous	32	8	24	13	11	7	4

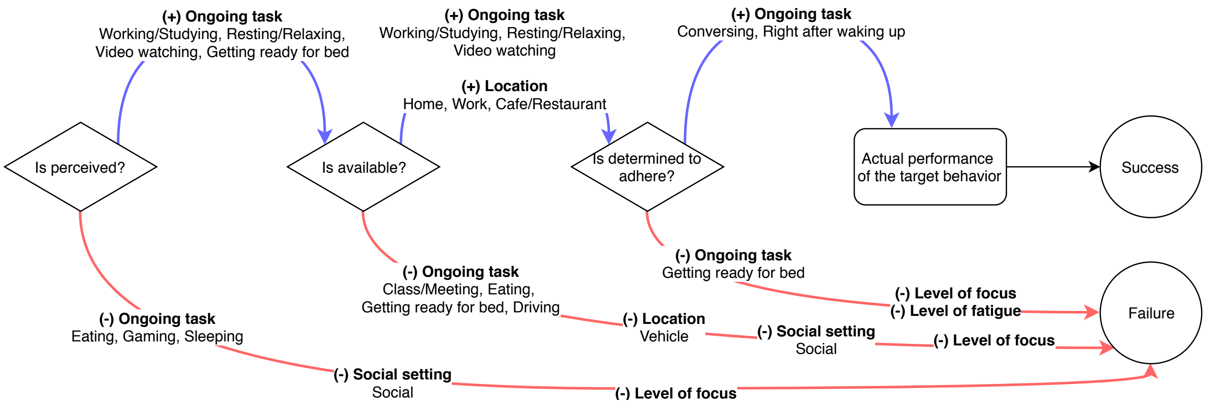
For ongoing tasks, we used the following major categories: *working/studying*, *sleeping*, *resting/relaxing*, *video watching*, *class/meeting*, *eating*, *gaming*, *conversing*, *getting ready for bed*, *calling/texting*, *right after waking up*, and *driving*. We differentiate gaming and video watching because gaming requires interactivity, whereas video watching is likely to be passive. While resting/relaxing, our participants were likely to sit on a couch or lie on a bed, possibly using their phones (e.g., reading news or checking social media). If the participants mentioned that they were playing games or watching videos while resting/relaxing, we excluded such instances from resting/relaxing and include them in gaming or video watching, because their level of focus would be generally higher than other resting activities.

Physical activities performed during a session of active breaks are categorized as follows: stretching/exercising, going for a walk, moving to other places, doing chores, visiting a restroom (for urination and defecation), water drinking, and bathing/washing. Because some responses included more than one physical activity (e.g., visiting a restroom and then going to a cafeteria), we put multiple categories into such responses.

6.3 Regression Analysis

We conducted multilevel logistic regression analysis to understand how a user's contextual factors affect different stages of the JIT intervention stage model (i.e., signal perception, availability assessment, and adherence to a

Fig. 5. Summary of regression analysis. "+" and "-" imply statistically significant dependent variables positively/negatively contributing to each decision stage, respectively.



target behavior). For each stage, we built a multilevel logistic regression model, where a dependent variable was a decision of the stage, and independent variables were contextual factors categorized and level of focus/fatigue (as fixed effects) and participants (as random intercepts). For the perception of the signal stage, we considered all responses, in which 2,051 instances were marked as perceived. The model for the assessment of availability accounted for those 2,051 perceived responses, where 1,657 were reported as available. For the adherence stage, we employed those 1,657 available instances, in which only 589 had active breaks. We reported the beta coefficient, odds ratio (OR) and confidence interval (CI) of each independent variable with fixed effects for different regression models. The goodness-of-fit of the model is computed with the marginal and conditional R^2, where marginal R^2 indicates variance explained by fixed effects and conditional one has variance explained by both fixed effects and random effects [54].

6.4 Qualitative Data Analysis

We conducted a thematic analysis of interview data to deepen understanding of the participants' behaviors during the field study. Two authors collaboratively performed affinity diagramming using ATLAS.ti Cloud[2]. We first conducted an open coding process in which codes were assigned to significant instances and references. This was performed with repeated iterations until consensus was reached between authors. We examined our coding schemes and analyzed relevant quotes to build rich descriptions and apposite examples of participants' behavioral patterns to corroborate our findings. In addition to the interview data analysis, we analyzed self-report data collected during the field study. The two authors conducted a thematic analysis for free-text responses for the question, "Why do you (not) stand up and move around for a minute?" to supplement interview data.

7 RESULTS

In this section, we present a result of our regression analysis corresponding to different decision stages of the JIT intervention model. We show dependent variables that have statistically significant contributions to each stage. Possible reasons for such contributions are explained with our interviews and self-reports. Fig. 5 describes a summary of our regression analysis results.

[2]https://atlasti.com/cloud/

Table 4. Results of logistic regression for perception of intervention signal ($^{*}p$<.05; $^{**}p$<.01; $^{***}p$<.001)

Predictors	β (SE)	z-statistic	95% CI for odds ratio			p	
			Lower	Odds ratio	Upper		
(intercept)	1.47 (0.35)	4.20	2.18	4.33	8.59	<.001	
Ongoing task							
Class/meeting	−0.04 (0.24)	−0.17	0.59	0.96	1.55	.862	
Conversing	−0.08 (0.30)	−0.27	0.51	0.92	1.67	.789	
Calling/texting	−0.11 (0.51)	−0.22	0.33	0.89	2.44	.824	
Working/studying	0.45 (0.18)	2.46	1.10	1.57	2.26	.014	*
Driving	−0.39 (0.95)	−0.41	0.10	0.67	4.34	.678	
Eating	−0.70 (0.25)	−2.84	0.30	0.49	0.80	.005	**
Resting/relaxing	−0.56 (0.21)	2.64	1.16	1.76	2.67	.008	**
Gaming	−0.53 (0.26)	−2.06	0.36	0.59	0.98	.040	*
Video watching	−0.91 (0.24)	3.74	1.54	2.48	4.00	<.001	***
Getting ready for bed	1.02 (0.46)	2.23	1.13	2.79	6.86	.026	*
Right after waking up	−0.76 (0.51)	−1.49	0.17	0.47	1.27	.136	
Location							
Home	0.01 (0.23)	0.05	0.65	0.67	1.58	.959	
Work	0.36 (0.24)	1.48	0.89	1.01	2.31	.138	
Restaurant/Cafe	0.05 (0.29)	0.18	0.60	1.44	1.86	.857	
Vehicle	−0.30 (0.75)	−0.40	0.74	1.05	3.20	.689	
Social setting							
Social	-0.35 (0.16)	-2.21	0.52	0.71	0.96	.027	*
Level of focus	−0.23 (0.06)	−3.65	0.70	0.79	0.90	<.001	***
Level of fatigue	−0.03 (0.05)	−0.54	0.87	0.97	1.08	.590	

7.1 RQ1. Factors Relevant to Perception of Intervention Signals

We first examined how the perception of intervention prompts were related to contextual factors and cognitive/physical states. Among 3,163 valid responses, we excluded responses marked as sleeping (n=565), because the participants did not perceive intervention prompts while sleeping. One predictor, which can completely predict the dependent variable, gives the largest standard error, leading to a misinterpretation of the model. The goodness-of-fit is .067 (marginal R^2) and .425 (conditional R^2). The regression result is shown in Table 4.

7.1.1 Contextual Factors Relevant to Perception. We found that participants significantly better perceived the intervention signals when they engaged in working/studying ($\beta = 0.45$, $OR = 1.57$, $p = .014$), resting/relaxing ($\beta = 0.56$, $OR = 1.76$, $p = .008$), video watching ($\beta = 0.91$, $OR = 2.48$, $p < .001$), and getting ready for bed ($\beta = 1.02$, $OR = 2.79$, $p = .026$). The possible reasons for better perception were that our participants often held or checked their smartphones during those tasks. For example, participants commented in self-reports as, *"watching YouTube videos with my smartphone" [P10], "watching TV and doing something with a smartphone"* [P22], and *"using my smartphone and about to go sleep"* [P22].

7.1.2 Contextual Factors Relevant to Missing. When participants were eating ($\beta = -0.70$, $OR = 0.49$, $p = .005$) and playing games ($\beta = -0.53$, $OR = 0.59$, $p = .040$), intervention signals were unlikely to be perceived. In the

Table 5. Results of logistic regression for perceived availability ($^{*}p$<.05; $^{**}p$<.01; $^{***}p$<.001)

Predictors	β (SE)	z-statistic	95% CI for odds ratio			p	
			Lower	Odds ratio	Upper		
(intercept)	0.21 (0.35)	0.58	0.62	1.23	2.45	.559	
Ongoing task							
Class/meeting	−3.01 (0.33)	−9.03	0.03	0.05	0.09	<.001	***
Conversing	−0.21 (0.31)	−0.68	0.44	0.81	1.48	.495	
Calling/texting	−0.70 (0.41)	−1.71	0.22	0.50	1.11	.088	
Working/studying	1.70 (0.22)	7.63	3.54	5.48	8.48	<.001	***
Eating	−0.62 (0.28)	−2.21	0.31	0.54	0.93	.027	*
Resting/relaxing	1.46 (0.30)	4.85	2.38	4.28	7.71	<.001	***
Gaming	0.17 (0.37)	0.47	0.58	1.19	2.45	.635	
Video watching	1.01 (0.26)	3.81	1.63	2.74	4.61	<.001	***
Getting ready for bed	−0.83 (0.37)	−2.23	0.21	0.44	0.91	.026	*
Right after waking up	1.51 (0.96)	1.58	0.69	4.54	9.81	.115	
Location							
Home	1.67 (0.23)	7.33	3.40	5.30	8.28	<.001	***
Work	1.24 (0.26)	4.76	2.07	3.44	5.72	<.001	***
Restaurant/Cafe	0.87 (0.30)	2.91	1.33	2.39	4.30	.004	**
Vehicle	−3.54 (0.67)	−5.28	0.01	0.03	0.11	<.001	***
Social setting							
Social	-0.49 (0.21)	-2.29	0.41	0.62	0.93	.022	*
Level of focus	−0.44 (0.08)	−5.56	0.55	0.64	0.75	<.001	***
Level of fatigue	0.05 (0.08)	0.70	0.91	1.06	1.23	.481	

interview, P12 said, *"I played a game mostly in an Internet cafe. It was too noisy and distracting. Also, I had to chat with friends to play the game."* Additionally, our participants definitely missed signals when they were sleeping.

Participants were more likely to miss intervention signals when they were in social settings ($\beta = -0.35$, $OR = 0.71, p = .027$). This might be partly explained using the perceptual load theory, where the perceptual system automatically consumes the limited perceptual capacity to process incoming information, and the information is missed when the capacity is exhausted [41]. The social setting likely accompanies interaction with others which might require higher demands on the perceptual system than solitary activities. Thus, our participants might be less likely to perceive the intervention signals.

7.1.3 Effects of Level of Focus and Fatigue on Perception/Missing. The level of focus has a statistically significant contribution to the signal being missing ($\beta = -0.23$, $OR = 0.79$, $p < .001$). This can be explained by the fact that the higher working memory load (possibly leading to a higher level of focus) attenuates to process irrelevant stimuli (i.e., smartphone notifications from our service) [70], resulting in missing prompts.

7.2 RQ2. Factors Relevant to Perceived Availability for Active Breaks

We now examine how participants' availability for engaging in active breaks was related to contextual factors and cognitive/physical states. Among the 2,051 perceived responses, we exclude 18 responses that mentioned types of ongoing tasks marked as driving, because those responses were answered as unavailable. The multilevel regression analysis was conducted with remaining 2,033 responses, as shown in Table 5. The marginal and conditional R^2 are .378 and .571, respectively.

7.2.1 Contextual Factors Relevant to Availability. For types of ongoing tasks, we found that three tasks (i.e., working/studying (β = 1.70, OR = 5.48, p < .001), resting/relaxing (β = 1.46, OR = 4.28, p < .001), and video watching (β = 1.01, OR = 2.74, p < .001)), show a statistically significant contribution to the availability to engage in active breaks. For location, participants were likely available to engage in active breaks at home (β = 1.67, OR = 5.30, p < .001), work (β = 1.24, OR = 3.44, p < .001), and restaurant/cafe (β = 0.87, OR = 2.39, p = .004). Because those contextual factors accounted for a greater portion of possible contexts in our self-report data (i.e., 58.4% and 95.3% of responses for types of ongoing tasks and location, respectively), we expect participants believed they were available to perform active breaks in most contexts.

7.2.2 Contextual Factors Relevant to Unavailability. We found that participants were unavailable to take an active break during class/meeting (β = −3.91, OR = 0.05, p < .001), eating (β = −0.62, OR = 0.54, p = .027), and getting ready for bed (β = −0.83, OR = 0.44, p = .026). Additionally, all driving tasks were reported as unavailable. Our interviews show possible reasons for unavailability. In a class/meeting, participants mostly were too conscious of others. In the interview, P12 noted, *"If I were to stand up [in a class], I would be spotted, and beyond that, I would be even asked to explain why I stand up."* While eating, most participants did not want to be disturbed, whereas there was no social pressure. For example, P11 noted in the interview, *"Doesn't it look strange to stand up while eating? I won't stop eating to stand."* For getting ready for bed, our participants felt it bothersome to take active breaks and marked in as unavailable As P20 answered in his self-reports, *"I was tired, so I lay down to take a nap and was using my phone right before sleeping on my bed. Then I received [the intervention signal]; it was bothersome."*

The regression results show that our participants were less likely to be available when they were in social settings (β = −0.49, OR = 0.62, p = .022). In particular, when participants were performing activities together, they were considered unavailable, because standing appeared to inappropriate. In the interview, P20 said, *"It is weird to suddenly stand up in the middle of conversing while drinking at the bar."* Another participant said, *"I don't even answer phone calls when I am with a professor. I just hang up."* [P19] Additionally, we found that, in some cases, participants did not want to interrupt social activities. For the watching activity, P23 said, *"At that moment, I could not stop, because I was watching a movie [at home] with my wife."* Furthermore, our participants almost unanimously said that they were not available for active breaks while in vehicles (β = −3.54, OR = 0.03, p < .001).

7.2.3 Effects of Level of Focus and Fatigue on Availability/Unavailability. The level of focus shows statistically significant contribution to unavailability (β = −0.44, OR = 0.64, p < .001). Whereas we showed that participants were more likely to stand up while working, there were also "unavailable" responses because of users' current focus on tasks at hand. In the interview, P18 mentioned, *"Once I have concentrated on my work, the flow of work should not be interrupted."*

7.3 RQ3. Factors Relevant to Adherence to Active Breaks

Our participants perceived intervention prompts and said that they were available to take active breaks, but that it did not always guarantee that they actually took active breaks. There were 1,657 responses (marked as perceived and available) out of which 589 prompts led to actual active breaks, leading to a success rate of 35.5%. We perform multilevel regression with 1,657 responses to identify factors related to active break adherence, as shown in Table 6. The goodness-of-fit of the model shows .145 for the marginal R^2 and .373 for the conditional R^2.

7.3.1 Contextual Factors Relevant to Adherence. Our regression analysis shows participants were more likely to take active breaks during conversations (β = 1.00, OR = 2.71, p = .010) or right after waking up (β = 2.42,

Table 6. Results of logistic regression for adherence to active breaks (*p<.05; **p<.01; ***p<.001)

Predictors	β (SE)	z-statistic	95% CI for odds ratio			p	
			Lower	Odds ratio	Upper		
(intercept)	−0.41 (0.42)	−0.98	0.29	0.66	1.50	.326	
Ongoing task							
Class/meeting	−1.18 (0.75)	−1.56	0.07	0.31	1.36	.120	
Conversing	1.00 (0.39)	2.58	1.27	2.71	5.78	.010	*
Calling/texting	0.21 (0.57)	0.37	0.40	1.23	3.76	.713	
Working/studying	0.20 (0.21)	0.97	0.82	1.22	1.83	.330	
Eating	0.07 (0.34)	0.21	0.55	1.07	2.08	.833	
Resting/relaxing	0.08 (0.23)	0.37	0.70	1.09	1.69	.713	
Gaming	−0.55 (0.44)	−1.25	0.24	0.58	1.37	.211	
Video watching	0.16 (0.24)	0.68	0.74	1.17	1.87	.499	
Getting ready for bed	−3.36 (0.95)	−3.53	0.01	0.03	0.22	<.001	***
Right after waking up	2.42 (0.58)	4.17	3.61	11.26	35.11	<.001	***
Location							
Home	0.05 (0.32)	0.14	0.55	1.05	1.98	.890	
Work	0.37 (0.33)	1.12	0.76	1.44	2.74	.263	
Restaurant/Cafe	−0.11 (0.37)	−0.31	0.43	0.89	1.86	.759	
Vehicle	0.88 (1.12)	0.78	0.27	2.41	21.77	.433	
Social setting							
Social	-0.02 (0.15)	-0.15	0.73	0.98	1.31	.877	
Level of focus	−0.45 (0.07)	−6.90	0.56	0.64	0.72	<.001	***
Level of fatigue	−0.22 (0.06)	−3.51	0.71	0.81	0.91	<.001	***

OR = 11.26, p < .001). This result somewhat contradicts our previous results, because a conversation is a social behavior, and active breaks hinder social interactions (thereby lowering availability). From the exit-interviews and self-report responses, we found several reasons for this discrepancy. First, conversing activities that were transitioned to active breaks happened to be simple chat session and were not serious discussions, as in a formal meeting. Our participants could easily stop chatting for active breaks. Alarms provided them with the excuse for finishing a conversation, particularly when they had planned follow-up activities. In the participants' self-reports, P23 noted, *"I was chit-chatting with my friends in a cafe [after lunch]. I was so full, and I wanted to move around."* P10 explained why he stood up, by saying *"I was chit-chatting with my colleague in the lab, and I was planning to go for a meal."* In the case of right after waking up, our participants mostly took active breaks to get out of the bed and prepare other activities. P14 commented in her self-report, *"I got up to go to the kitchen to have breakfast."* P10 stated, *"In my dormitory, I got up for washing."*

Besides contextual factors, our interview analysis shows that participants took active breaks for the purpose of mental refreshment. P20 said, *"Sometimes it is boring to study. I'd like to stand when studying."* Additionally, health beliefs in active breaks are positive motivators of adherence. P21 said, *"I often received notifications when I was watching TV, during online lectures, or when watching YouTube videos. I tried to keep moving. If there were no alarms, I would have mostly continued sitting without realizing that my legs hurt. I like the fact that this app helps me keep moving my legs."*

Table 7. Physical activities during active breaks

Type	Example	N = 589
Visiting a restroom	Urination and defecation	200 (34.0%)
Water drinking	To sip water	95 (16.1%)
Moving to other places	To commute to work/school, to go to the hospital	83 (14.1%)
Doing chores	Dish-washing, cleaning	81 (13.8%)
Going for a walk	Walking around	71 (12.1%)
Stretching/exercising	Stretching neck	55 (9.3%)
Bathing/washing	To wash face, to brush teeth	50 (8.5%)
Miscellaneous	To turn light off, to change clothes	22 (3.7%)

7.3.2 Contextual Factors Relevant to Rejection. Participants were less likely to take active breaks when they were about to go to bed ($\beta = -3.36$, $OR = 0.03$, $p < .001$). Interestingly, this activity was also frequently marked as unavailable, whereas our participants sometimes judged that they would be available for moving. Despite such availability judgments, our participants tended to ignore notifications, because they were ready to asleep and wanted to stay in bed. For example, P3 answered in her self-reports, *"I was in my room alone. I was about to sleep with lights off, web surfing in the bed."*

7.3.3 Effects of Level of Focus and Fatigue on Adherence/Rejection. The regression results show that our participants were less likely to take active breaks when the level of focus or the level of fatigue was high ($\beta = -0.45$, $OR = 0.64$, $p < .001$, and $\beta = -0.22$, $OR = 0.81$, $p < .001$, respectively). Whereas they perceived the alarms and believe that they would be available, it seems that performing active breaks is highly dependent on their levels of focus and fatigue. In the interview, P14 wanted to continue concentrating on work, by saying *"I might lose concentration if I do (an active break) while working. Thus, I just kept working."* Another participant also commented, *"The alarm rang when I was really focused on writing a report (at work). I was working alone, so I was able to stand up. But I did not want to break the flow, so I didn't stand up."* [P7] Regarding level of fatigue, P18 stated, *"After working hard during the weekdays, I felt burned-out during the weekend. I want to lie down or use computers to take some rest. Anyway, I can stand up after receiving an alarm message, but..."* P7 also said that he did not take active breaks when watching TV dramas and getting rest, *"Because, actually, it was so tiring and troublesome."*

7.4 RQ4: Physical Activities Performed during Active Breaks

Table 7) shows physical activities performed during active breaks. Interestingly, our participants mostly took active breaks for physiological needs (e.g., 34.2% for visiting a restroom and 16.1% for drinking water), rather than precise health-related reasons (e.g., 9.3% for stretching/exercising). Indeed, prompt delivery worked as a trigger for the transition between routine and planned behaviors. In the interview, P4 said, *"I have postponed to go to a restroom because I felt lazy. But when the smartphone alarm sounds, I visited the restroom while I was standing up and walking around."*

8 DISCUSSION

JIT interventions are known to be complex processes involving human information processing and behavior controlling for adherence [52]. Investigating how people respond to incoming JIT support messages is of great interest to the Ubicomp community because of its close relationship with interruptibility research (e.g., finding opportune moments for delivering notifications). Building upon prior studies of interruptibility [74, 75], our work deepened the understanding of receptivity by proposing a JIT intervention stage model that detailed receptivity in four stages: perception, availability, adherence, and performance. After building a mobile JIT service to prevent prolonged sedentary behaviors, we conducted regression analyses with the self-reported contexts and cognitive/physical states collected over 3 weeks. Then, we corroborated our findings via in-depth interviews. Our results showed that the level of focus had a negative relationship across all stages, and fatigue was one of the major factors affecting adherence. Whereas prior JIT studies only considered simple cases for availability (e.g., already performing target behaviors or in unsafe situations, such as driving) [37], our work showed that availability was multifaceted and context-dependent. Unlike an office setting, we showed that mobile intervention must carefully consider various ongoing tasks at different places. As indicated in a prior work [45], participants perform diverse physical activities during active breaks. From our findings, we discuss several design implications.

8.1 Considering "Available, But Not Adhering To" Cases

Whereas participants said that they were available, two-thirds of JIT prompts failed to inspire adherence to the behaviors suggested, owing to higher levels of ongoing task engagement and physical fatigue or getting ready for bed. Such results highlight that it is critical to better differentiate availability and adherence. When users do not adhere to JIT support (assuming it is perceived), prior studies on interruptibility that considered only final resulting responses did not differentiate whether users were available or did not want to perform the behavior suggested. Different decisions underlying final decisions provide great opportunities for building persuasive systems for promoting health behaviors. For example, if there are limited opportunities for prompting users to limit user burdens and prevent disengagement of interventions [43], we can better prioritize intervention contexts to times when users are available. Additionally, given available contexts, we can more rigorously test effects of different contents on JIT support (e.g., walking vs. anti-sedentary suggestions) on adherence to interventions and health-related outcomes [37]. Considering available contexts, we can exquisitely design intelligent interventions to increase levels of adherence by dynamically changing persuasive elements (e.g., incentives) or learning users' preference for suggestions [62].

8.2 Providing Contextually Tailored and Personalized Guidelines

Our findings on factors relevant to availability parallels six elements of simplicity in FBM: time, money, physical effort, brain cycles, social deviance, and non-routine [24]. Our participants believed they would unavailable to stand up and move around when such behavior goes against the norm (e.g., standing up during a meeting or a class), is not routine (e.g., standing up while getting ready for bed or eating), and disrupts their concentration. Such results imply that we can enhance availability by providing different behavioral guidelines with simplicity elements. For example, JIT health intervention suggests collaborative behaviors resulting in certain health benefits, such as walking meetings [2]. This may establish shared norms about the target behaviors so that social deviance may be reduced.

Additionally, participants' practices during active breaks suggest interesting implications. Our participants tended to engage in their routine tasks accompanying physical activities, such as visiting a restroom or sipping water. Such findings highlight that we can provide different behavioral guidelines resulting in similar health outcomes regarding users' routine behaviors and contexts. For example, we can deliver JIT prompts that suggest to getting a drink of water or visiting a restroom on a regular basis. Whereas these suggestions seem irrelevant to sedentary behaviors, they would provide similar health outcomes if users would adhere to suggestions. Such varying suggestions could mitigate habituation to interventions [43].

8.3 Inferring Receptivity of JIT Support

Our JIT stage model provides an opportunity to separately model perception, availability, and adherence. In addition, our regression analysis showed that contextual factors and cognitive/physical states are good predictors of each decision point. Leveraging prior Ubicomp literature on context awareness, such as activity recognition [20], location tracking [35], emotion sensing [11], and even circadian rhythms [1, 46], we can automatically detect opportune moments for JIT support. Specifically, our findings on factors relevant to availability indicate that official and important work schedules can negatively influence on availability. Thus, users' calendar informations can be used to predict availability [44]. Besides passive sensing and self-reports, we can embed various small tasks as part of typical user interactions to infer users' status (e.g., alertness tracking with vigilance tasks) as in cognition-aware systems [19].

9 LIMITATIONS AND FUTURE WORK

There were several limitations of the present study. Our intervention stage model may not fully capture the *real cognitive process of human beings* when they are given JIT support. The model basically assumes that a user goes through a sequence of micro-decisions when reacting to a given JIT support message. While the perception stage is obviously the first decision point, the other two decisions (i.e., availability and adherence) may happen either successively (but even in the opposite order) or in parallel. The current work hypothesized that these steps exist, and we attempted to validate that through self-reports collection and statistical analysis. According to the dual-process accounts of reasoning, an individual's reasoning for action is governed by System 1 (i.e., fast, automatic, emotional reasoning) and System 2 (i.e., slow, conscious, controlled judgments) [21]. Automatic and controlled cognitive operations that compete with one another in determining behavioral choices. Our self-reports (possibly done when they are available to answer) could have made the participants switch to System 2, which helped them to carefully reflect upon their decision making processes. In practice, however, at the time of receiving a JIT support message, it may be possible that users' reasoning could be dominated by System 1. For example, users who are less motivated and feel tired may immediately reject the suggestion without carefully assessing their availability. Even in this case, there may be no clear distinction between the availability assessment and adherence determination stages. Further studies are required in order to better understand human reasoning in JIT intervention. One interesting future study would be comparing user responses based on answering delay, assuming that immediate responses are more influenced by System 1 than belated responses. Despite such methodological limitations, our efforts provided a pragmatic framework that helps researchers to understand the receptivity to JIT support. Our findings imply how ubiquitous technologies can better differentiate availability and adherence, possibly leading to advanced JIT intervention design that reduces the user's burden and provides highly motivated suggestions.

Another limitation is that our model only details decisions over a single JIT intervention. However, for successful health behavior treatments, it is important to achieve retention of JIT intervention. Prior studies have shown that retention reflects motivational issues and intervention fatigue issues [53]. Long-term user studies that model those variables will help us better understand receptivity to JIT intervention. Furthermore, this work only considers a limited number of factors relevant to receptivity to JIT support. Although our results clearly highlight contextual factors contributing to the perception and availability stages, there is still a lack of understanding about how motivational or other potential factors impact adherence to given JIT support. Because JIT support can increase motivation itself (i.e., *spark as trigger* in FBM [24]), further studies should investigate motivation that both an individual originally has and that JIT intervention promotes.

10 CONCLUSION

We extended previous interruptibility models to deepen our understanding of receptivity for mobile JIT intervention. The extended stage model comprised four stages: message perception, availability assessment, adherence determination, and actual behavior execution. We built a mobile JIT intervention system to prevent prolonged sedentary behaviors and collected self-reported context and decision data from a 3-week field trial. We systematically explored various contextual factors relevant to each stage outcome using quantitative and qualitative data analyses. We found that availability for JIT intervention is multifaceted and context-dependent, and contextual factors affecting availability significantly differed from adherence. Mobile JIT health intervention is prevalent nowadays. We believe that our work makes an important step toward deepening the field's understanding of receptivity for these technologies. Our findings also provide novel opportunities for building less disruptive, but more effective methods for mobile JIT health intervention.

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REFERENCES

[1] Saeed Abdullah, Mark Matthews, Elizabeth L. Murnane, Geri Gay, and Tanzeem Choudhury. 2014. Towards Circadian Computing: "Early to Bed and Early to Rise" Makes Some of Us Unhealthy and Sleep Deprived. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. ACM, 673–684. https://doi.org/10.1145/2632048.2632100

[2] A. Ahtinen, E. Andrejeff, C. Harris, and K. Väänänen. 2017. Let's Walk at Work: Persuasion Through the Brainwolk Walking Meeting App. In *Proceedings of the 21st International Academic Mindtrek Conference (AcademicMindtrek '17)*. ACM, 73–82. https://doi.org/10.1145/3131085.3131098

[3] Taleb A. Alkhajah, Marina M. Reeves, Elizabeth G. Eakin, Elisabeth A.H. Winkler, Neville Owen, and Genevieve N. Healy. 2012. Sit-Stand Workstations: A Pilot Intervention to Reduce Office Sitting Time. *American Journal of Preventive Medicine* 43, 3 (Sept. 2012), 298–303. https://doi.org/10.1016/j.amepre.2012.05.027

[4] Daniel Avrahami and Scott E. Hudson. 2006. Responsiveness in Instant Messaging: Predictive Models Supporting Inter-personal Communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, 731–140. https://doi.org/10.1145/1124772.1124881

[5] Sangwon Bae, Anind K. Dey, and Carissa A. Low. 2016. Using Passively Collected Sedentary Behavior to Predict Hospital Readmission. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. ACM, 616–621. https://doi.org/10.1145/2971648.2971750

[6] Avner Ben-Ner, Darla J. Hamann, Gabriel Koepp, Chimnay U. Manohar, and James Levine. 2014. Treadmill Workstations: The Effects of Walking while Working on Physical Activity and Work Performance. *PLoS ONE* 9, 2 (Feb. 2014), e88620. https://doi.org/10.1371/journal.pone.0088620

[7] Aviroop Biswas, Paul I. Oh, Guy E. Faulkner, Ravi R. Bajaj, Michael A. Silver, Marc S. Mitchell, and David A. Alter. 2015. Sedentary Time and Its Association With Risk for Disease Incidence, Mortality, and Hospitalization in Adults. *Annals of Internal Medicine* 162, 2 (Jan. 2015), 123–132. https://doi.org/10.7326/M14-1651

[8] Dale S. Bond, J. Graham Thomas, Hollie A. Raynor, Jon Moon, Jared Sieling, Jennifer Trautvetter, Tiffany Leblond, and Rena R. Wing. 2014. B-MOBILE - A Smartphone-Based Intervention to Reduce Sedentary Iime in Overweight/Obese Individuals: A Within-Subjects Experimental Trial. *PLoS ONE* 9, 6 (2014). https://doi.org/10.1371/journal.pone.0100821

[9] Andreas Braun, Ingrid Schembri, and Sebastian Frank. 2015. ExerSeat - Sensor-Supported Exercise System for Ergonomic Microbreaks. In *Ambient Intelligence*. Springer International Publishing, 236–251. https://doi.org/10.1007/978-3-319-26005-1_16

[10] Scott A. Cambo, Daniel Avrahami, and Matthew L. Lee. 2017. BreakSense: Combining Physiological and Location Sensing to Promote Mobility during Work-Breaks. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, 3595–3607. https://doi.org/10.1145/3025453.3026021

[11] Bokai Cao, Lei Zheng, Chenwei Zhang, Philip S. Yu, Andrea Piscitello, John Zulueta, Olu Ajilore, Kelly Ryan, and Alex D. Leow. 2017. DeepMood: Modeling Mobile Phone Typing Dynamics for Mood Detection. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '17)*. ACM, 747–755. https://doi.org/10.1145/3097983.3098086

[12] Lucas J. Carr, Kristina Karvinen, Mallory Peavler, Rebecca Smith, and Kayla Cangelosi. 2013. Multicomponent Intervention to Reduce Daily Sedentary Time: A Randomised Controlled Trial. *BMJ Open* 3, 10 (Oct. 2013), e003261. https://doi.org/10.1136/bmjopen-2013-003261

[13] Yung-Ju Chang and John C. Tang. 2015. Investigating Mobile Users' Ringer Mode Usage and Attentiveness and Responsiveness to Communication. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, 6–15. https://doi.org/10.1145/2785830.2785852

[14] Woohyeok Choi, Jeongmin Oh, Darren Edge, Joohyun Kim, and Uichin Lee. 2016. SwimTrain: Exploring Exergame Design for Group Fitness Swimming. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, 1692–1704. https://doi.org/10.1145/2858036.2858579

[15] Woohyeok Choi, Jeungmin Oh, Taiwoo Park, Seongjun Kang, Miri Moon, Uichin Lee, Inseok Hwang, Darren Edge, and Junehwa Song. 2016. Designing Interactive Multiswimmer Exergames. *ACM Transactions on Sensor Networks* 12, 3 (July 2016), 1–40. https://doi.org/10.1145/2888399

[16] Sunny Consolvo, Katherine Everitt, Ian Smith, and James A. Landay. 2006. Design Requirements for Technologies That Encourage Physical Activity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, 457–466. https://doi.org/10.1145/1124772.1124840

[17] Sunny Consolvo, Ryan Libby, Ian Smith, James A. Landay, David W. McDonald, Tammy Toscos, Mike Y. Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, and Louis LeGrand. 2008. Activity Sensing in the Wild: A Field Trial of Ubifit Garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, 1797–1806. https://doi.org/10.1145/1357054.1357335

[18] Ding, Xu, Wang, Chen, Thind, and Zhang. 2016. WalkMore: Promoting Walking with Just-In-Time Context-Aware Prompts. In *2016 IEEE Wireless Health (WH '16)*. IEEE, 1–8. https://doi.org/10.1109/WH.2016.7764558

[19] Tilman Dingler, Albrecht Schmidt, and Tonja Machulla. 2017. Building Cognition-Aware Systems: A Mobile Toolkit for Extracting Time-of-Day Fluctuations of Cognitive Performance. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (Sept. 2017), 47:1–47:15. https://doi.org/10.1145/3132025

[20] Genevieve Dunton, Eldin Dzubur, Keito Kawabata, Brenda Yanez, Bin Bo, and Stephen Intille. 2014. Development of a Smartphone Application to Measure Physical Activity Using Sensor-Assisted Self-Report. *Frontiers in Public Health* 2 (March 2014), 12. https://doi.org/10.3389/fpubh.2014.00012

[21] Jonathan St.B.T. Evans. 2003. In Two Minds: Dual-Process Accounts of Reasoning. *Trends in Cognitive Sciences* 7, 10 (Oct. 2003), 454–459. https://doi.org/10.1016/J.TICS.2003.08.012

[22] Joel E. Fischer, Chris Greenhalgh, and Steve Benford. 2011. Investigating Episodes of Mobile Phone Activity As Indicators of Opportune Moments to Deliver Notifications. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. ACM, 181. https://doi.org/10.1145/2037373.2037402

[23] Joel E. Fischer, Nick Yee, Victoria Bellotti, Nathan Good, Steve Benford, and Chris Greenhalgh. 2010. Effects of Content and Time of Delivery on Receptivity to Mobile Interruptions. In *Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '10)*. ACM, 103–112. https://doi.org/10.1145/1851600.1851620

[24] B. J. Fogg. 2009. A Behavior Model for Persuasive Design. In *Proceedings of the 4th International Conference on Persuasive Technology (Persuasive '09)*. ACM, New York, New York, USA, 40:1–40:7. https://doi.org/10.1145/1541948.1541999

[25] Jutta Fortmann, Tim Stratmann, Susanne Boll, Benjamin Poppinga, and Wilko Heuten. 2013. Make Me Move at Work! An Ambient Light Display to Increase Physical Activity. In *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops*. IEEE, 274–277. https://doi.org/10.4108/icst.pervasivehealth.2013.252089

[26] Derek Foster, Conor Linehan, and Shaun Lawson. 2010. Motivating Physical Activity at Work: Using Persuasive Social Media Extensions for Simple Mobile Devices. *CEUR Workshop Proceedings* 690 (2010), 11–14. https://doi.org/10.1145/1930488.1930510

[27] Nicholas D. Gilson, Norman Ng, Toby G. Pavey, Gemma C. Ryde, Leon Straker, and Wendy J. Brown. 2016. Project Energise: Using Participatory Approaches and Real Time Computer Prompts to Reduce Occupational Sitting and Increase Work Time Physical Activity in Office Workers. *Journal of Science and Medicine in Sport* 19, 11 (2016), 926–930. https://doi.org/10.1016/j.jsams.2016.01.009

[28] Genevieve N. Healy, David W. Dunstan, Jo Salmon, Ester Cerin, Jonathan E. Shaw, Paul Z. Zimmet, and Neville Owen. 2008. Breaks in Sedentary Time: Beneficial Associations with Metabolic Risk. *Diabetes Care* 31, 4 (April 2008), 661–666. https://doi.org/10.2337/dc07-2046

[29] Sen H. Hirano, Robert G. Farrell, Catalina M. Danis, and Wendy A. Kellogg. 2013. WalkMinder: Encouraging an Active Lifestyle Using Mobile Phone Interruptions. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, 1431–1436. https://doi.org/10.1145/2468356.2468611

[30] Eric Horvitz, Pau Koch, Carl M. Kadie, and Andy Jacobs. 2002. Coordinate: Probabilistic Forecasting of Presence and Availability. In *Proceedings of the Eighteenth Conference on Uncertainty in Artificial Intelligence (UAI '02)*. Morgan Kaufmann Publishers Inc., 224–233. http://dl.acm.org/citation.cfm?id=2073876.2073903

[31] Hayeon Jeong, Heepyung Kim, Rihun Kim, Uichin Lee, and Yong Jeong. 2017. Smartwatch Wearing Behavior Analysis: A Longitudinal Study. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3 (Sept. 2017), 60:1–60:31. https://doi.org/10.1145/3131892

[32] Dinesh John, Dixie L. Thompson, Hollie Raynor, Kenneth M. Bielak, and David R. Bassett. 2010. Effects of Treadmill Workstations as a Worksite Physical Activity Intervention in Overweight and Obese Office Workers. *Medicine & Science in Sports & Exercise* 42 (May 2010), 38. https://doi.org/10.1249/01.MSS.0000384859.60808.5c

[33] Darla E. Kendzor, Kerem Shuval, Kelley Pettee Gabriel, Michael S. Businelle, Ping Ma, Robin R. High, Erica L. Cuate, Insiya B. Poonawalla, Debra M. Rios, Wendy Demark-Wahnefried, Michael D. Swartz, and David W. Wetter. 2016. Impact of a Mobile Phone Intervention to Reduce Sedentary Behavior in a Community Sample of Adults: A Quasi-Experimental Evaluation. *Journal of medical Internet research* 18, 1 (2016), e19. https://doi.org/10.2196/jmir.5137

[34] Auk Kim, Woohyeok Choi, Jungmi Park, Kyeyoon Kim, and Uichin Lee. 2018. Interrupting Drivers for Interactions: Predicting Opportune Moments for In-vehicle Proactive Auditory-verbal Tasks. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4 (Dec. 2018), 175:1–175:28. https://doi.org/10.1145/3287053

[35] Donnie H. Kim, Younghun Kim, Deborah Estrin, and Mani B. Srivastava. 2010. SensLoc: Sensing Everyday Places and Paths Using Less Energy. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems (SenSys '10)*. ACM, 43–56. https://doi.org/10.1145/1869983.1869989

[36] Predrag Klasnja, Eric B Hekler, Saul Shiffman, Audrey Boruvka, Daniel Almirall, Ambuj Tewari, and Susan A Murphy. 2015. Microrandomized trials: An experimental design for developing just-in-time adaptive interventions. *Health psychology : official journal of the Division of Health Psychology, American Psychological Association* 34S, 0 (Dec. 2015), 1220–8. https://doi.org/10.1037/hea0000305

[37] Predrag Klasnja, Shawna Smith, Nicholas J Seewald, Andy Lee, Kelly Hall, Brook Luers, Eric B Hekler, and Susan A Murphy. 2018. Efficacy of Contextually Tailored Suggestions for Physical Activity: A Micro-randomized Optimization Trial of HeartSteps. *Annals of Behavioral Medicine* (Sept. 2018). https://doi.org/10.1093/abm/kay067

[38] Rafal Kocielnik, Lillian Xiao, Daniel Avrahami, and Gary Hsieh. 2018. Reflection Companion: A Conversational System for Engaging Users in Reflection on Physical Activity. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 2 (July 2018), 70:1–70:26. https://doi.org/10.1145/3214273

[39] Kara A. Latorella. 1999. *Investigating Interruptions: Implications for Flightdeck Performance.* Technical Report. NASA Langley Research Center, Hampton, VA United States. https://ntrs.nasa.gov/search.jsp?R=20000004291

[40] Nilli Lavie. 2010. Attention, Distraction, and Cognitive Control Under Load. *Current Directions in Psychological Science* 19, 3 (2010), 143–148. https://doi.org/10.1177/0963721410370295

[41] Nilli Lavie, Aleksandra Hirst, Jan W. de Fockert, and Essi Viding. 2004. Load Theory of Selective Attention and Cognitive Control. *Journal of Experimental Psychology: General* 133, 3 (Sept. 2004), 339–354. https://doi.org/10.1037/0096-3445.133.3.339

[42] Uichin Lee, Kyungsik Han, Hyunsung Cho, Kyong-Mee Chung, Hwajung Hong, Sung-Ju Lee, Youngtae Noh, Sooyoung Park, and John M." Carroll. 2019. Intelligent Positive Computing with Mobile, Wearable, and IoT Devices: Literature Review and Research Directions. *Ad Hoc Networks* 83 (Feb. 2019), 8–24. https://doi.org/10.1016/j.adhoc.2018.08.021

[43] Peng Liao, Walter Dempsey, Hillol Sarker, Syed Monowar Hossain, Mustafa Al'Absi, Predrag Klasnja, and Susan Murphy. 2018. Just-in-Time but Not Too Much: Determining Treatment Timing in Mobile Health. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (Dec. 2018), 179:1–179:21. https://doi.org/10.1145/3287057

[44] Tom Lovett, Eamonn O'Neill, James Irwin, and David Pollington. 2010. The Calendar as a Sensor: Analysis and Improvement Using Data Fusion with Social Networks and Location. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing (UbiComp '10)*. ACM, 3–12. https://doi.org/10.1145/1864349.1864352

[45] Yuhan Luo, Bongshin Lee, Donghee Yvette Wohn, Amanda L. Rebar, David E. Conroy, and Eun Kyoung Choe. 2018. Time for Break: Understanding Information Workers' Sedentary Behavior Through a Break Prompting System. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, New York, USA, 1–14. https://doi.org/10.1145/3173574.3173701

[46] Gloria Mark, Yiran Wang, Melissa Niiya, and Stephanie Reich. 2016. Sleep Debt in Student Life: Online Attention Focus, Facebook, and Mood Gloria. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, 5517–5528. https://doi.org/10.1145/2858036.2858437

[47] Shelly K McCrady and James A Levine. 2009. Sedentariness at Work: How Much Do We Really Sit? *Obesity* 17, 11 (Nov. 2009), 2103–2105. https://doi.org/10.1038/oby.2009.117

[48] Abhinav Mehrotra, Sandrine R. Müller, Gabriella M. Harari, Samuel D. Gosling, Cecilia Mascolo, Mirco Musolesi, and Peter J. Rentfrow. 2017. Understanding the Role of Places and Activities on Mobile Phone Interaction and Usage Patterns. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (Sept. 2017), 84:1–84:22. https://doi.org/10.1145/3131901

[49] Abhinav Mehrotra, Mirco Musolesi, Robert Hendley, and Veljko Pejovic. 2015. Designing Content-Driven Intelligent Notification Mechanisms for Mobile Applications. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, 813–824. https://doi.org/10.1145/2750858.2807544

[50] Abhinav Mehrotra, Veljko Pejovic, Jo Vermeulen, Robert Hendley, and Mirco Musolesi. 2016. My Phone and Me: Understanding People's Receptivity to Mobile Notifications. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM,

1021–1032. https://doi.org/10.1145/2858036.2858566

[51] Florian Floyd Mueller, Martin R. Gibbs, Frank Vetere, and Darren Edge. 2017. Designing for Bodily Interplay in Social Exertion Games. *ACM Transactions on Computer-Human Interaction* 24, 3 (May 2017), 1–41. https://doi.org/10.1145/3064938

[52] Inbal Nahum-Shani, Eric B Hekler, and Donna Spruijt-Metz. 2015. Building Health Behavior Models to Guide the Development of Just-In-Time Adaptive Interventions: A Pragmatic Framework. *Health Psychologysychology* 34S, 0 (Dec. 2015), 1209–19. https://doi.org/10.1037/hea0000306

[53] Inbal Nahum-Shani, Shawna N Smith, Bonnie J Spring, Linda M Collins, Katie Witkiewitz, Ambuj Tewari, and Susan A Murphy. 2016. Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine* (Sept. 2016). https://doi.org/10.1007/s12160-016-9830-8

[54] Shinichi Nakagawa and Holger Schielzeth. 2013. A General and Simple Method for Obtaining Rˆ2 from Generalized Linear Mixed-effects Models. *Methods in Ecology and Evolution* 4, 2 (Feb. 2013), 133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x

[55] Felix Naughton, Sarah Hopewell, Neal Lathia, Rik Schalbroeck, Chloë Brown, Cecilia Mascolo, Andy McEwen, and Stephen Sutton. 2016. A Context-Sensing Mobile Phone App (Q Sense) for Smoking Cessation: A Mixed-Methods Study. *JMIR mHealth and uHealth* 4, 3 (Sept. 2016), e106. https://doi.org/10.2196/mhealth.5787

[56] Neville Owen, Geneviève N Healy, Charles E Matthews, and David W Dunstan. 2010. Too Much Sitting: The Population-Health Science of Sedentary Behavior. *Exercise and sport sciences reviews* 38, 3 (July 2010), 105–13. https://doi.org/10.1097/JES.0b013e3181e373a2

[57] Scott J. Pedersen, Paul D. Cooley, and Casey Mainsbridge. 2014. An e-Health Intervention Designed to Increase Workday Energy Expenditure by Reducing Prolonged Occupational Sitting Habits. *Work* 49, 2 (2014), 289–295. https://doi.org/10.3233/WOR-131644

[58] Veljko Pejovic and Mirco Musolesi. 2014. InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. ACM, 897–908. https://doi.org/10.1145/2632048.2632062

[59] Martin Pielot, Bruno Cardoso, Kleomenis Katevas, Joan Serrà, Aleksandar Matic, and Nuria Oliver. 2017. Beyond Interruptibility: Predicting Opportune Moments to Engage Mobile Phone Users. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (Sept. 2017), 91:1–91:25. https://doi.org/10.1145/3130956

[60] Laura Pina, Ernesto Ramirez, and William Griswold. 2012. Fitbit+: A Behavior-based Intervention System to Reduce Sedentary Behavior. In *Proceedings of the 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth '12)*. IEEE, 175–178. https://doi.org/10.4108/icst.pervasivehealth.2012.248761

[61] Laura Pina, Kael Rowan, Paul Johns, Asta Roseway, Gillian Hayes, and Mary Czerwinski. 2014. In Situ Cues for ADHD Parenting Strategies Using Mobile Technology. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcar (PervasiveHealth '14)*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 17–24. https://doi.org/10.4108/icst.pervasivehealth.2014.254958

[62] Mashfiqui Rabbi, Min Hane Aung, Mi Zhang, and Tanzeem Choudhury. 2015. MyBehavior: Automatic Personalized Health Feedback from User Behaviors and Preferences using Smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '15*. ACM, New York, New York, USA, 707–718. https://doi.org/10.1145/2750858.2805840

[63] Tauhidur Rahman, Mary Czerwinski, Ran Gilad-Bachrach, and Paul Johns. 2016. Predicting "About-to-Eat" Moments for Just-in-Time Eating Intervention. In *Proceedings of the 6th International Conference on Digital Health Conference (DH '16)*. ACM, 141–150. https://doi.org/10.1145/2896338.2896359

[64] Jun Rekimoto and Hitomi Tsujita. 2014. Inconvenient Interactions: An Alternative Interaction Design Approach to Enrich Our Daily Activities. In *Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces (AVI '14)*. ACM, 225–228. https://doi.org/10.1145/2598153.2598196

[65] Irwin M. Rosenstock. 1974. The Health Belief Model and Preventive Health Behavior. *Health Education Monographs* 2, 4 (Dec. 1974), 354–386. https://doi.org/10.1177/109019817400200405

[66] Sherwood W. Samn and Layne P. Perelli. 1982. *Estimating Aircrew Fatigue: A Technique with Application to Airlift Operations*. Technical Report. Brooks AFB, TX: USAF School of Aerospace Medicine. http://www.dtic.mil/docs/citations/ADA125319

[67] Hillol Sarker, Karen Hovsepian, Soujanya Chatterjee, Inbal Nahum-Shani, Susan A. Murphy, Bonnie Spring, Emre Ertin, Mustafa Al'Absi, Motohiro Nakajima, and Santosh Kumar. 2017. From Markers to Interventions: The Case of Just-in-Time Stress Intervention. In *Mobile Health: Sensors, Analytic Methods, and Applications*. Springer International Publishing, 411–433. https://doi.org/10.1007/978-3-319-51394-2_21

[68] Hillol Sarker, Moushumi Sharmin, Amin Ahsan Ali, Md. Mahbubur Rahman, Rummana Bari, Syed Monowar Hossain, and Santosh Kumar. 2014. Assessing the Availability of Users to Engage in Just-In-Time Intervention in the Natural Environment. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. ACM, 909–920. https://doi.org/10.1145/2632048.2636082

[69] Joon-Gi Shin, Eiji Onchi, Maria Jose Reyes, Junbong Song, Uichin Lee, Seung-Hee Lee, and Daniel Saakes. 2019. Slow Robots for Unobtrusive Posture Correction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, 613:1–613:10. https://doi.org/10.1145/3290605.3300843

[70] Patrik Sörqvist, Stefan Stenfelt, and Jerker Rönnberg. 2012. Working Memory Capacity and Visual–Verbal Cognitive Load Modulate Auditory–Sensory Gating in the Brainstem: Toward a Unified View of Attention. *Journal of Cognitive Neuroscience* 24, 11 (Nov. 2012), 2147–2154. https://doi.org/10.1162/jocn_a_00275

[71] Takemi Sugiyama, Genevieve N. Healy, David W. Dunstan, Jo Salmon, and Neville Owen. 2008. Joint Associations of Multiple Leisure-Time Sedentary Behaviours and Physical Activity with Obesity in Australian Adults. *The International Journal of Behavioral Nutrition and Physical Activity* 5 (July 2008), 35. https://doi.org/10.1186/1479-5868-5-35

[72] J. Graham Thomas and Dale S. Bond. 2015. Behavioral Response to a Just-in-time Adaptive Intervention (JITAI) to Reduce Sedentary Behavior in Obese Adults: Implications for JITAI Optimization. *Health Psychology* 34, Suppl (Dec. 2015), 1261–1267. https://doi.org/10.1037/hea0000304

[73] Alicia A Thorp, Genevieve N Healy, Elisabeth Winkler, Bronwyn K Clark, Paul A Gardiner, Neville Owen, and David W Dunstan. 2012. Prolonged Sedentary Time and Physical Activity in Workplace and Non-Work Contexts: A Cross-Sectional Study of Office, Customer Service and Call Centre Employees. *International Journal of Behavioral Nutrition and Physical Activity* 9, 1 (2012), 128. https://doi.org/10.1186/1479-5868-9-128

[74] Liam D. Turner, Stuart M. Allen, and Roger M. Whitaker. 2015. Push or Delay? Decomposing Smartphone Notification Response Behaviour. In *Proceedings of the 6th International Workshop on Human Behavior Understanding - Volume 927*. Springer-Verlag, 69–83. https://doi.org/10.1007/978-3-319-24195-1_6

[75] Liam D. Turner, Stuart M. Allen, and Roger M. Whitaker. 2017. Reachable but not Receptive: Enhancing Smartphone Interruptibility Prediction by Modelling the Extent of User Engagement with Notifications. *Pervasive and Mobile Computing* 40 (Sept. 2017), 480–494. https://doi.org/10.1016/J.PMCJ.2017.01.011

[76] Saskia van Dantzig, Gijs Geleijnse, and Aart Tijmen van Halteren. 2013. Toward a Persuasive Mobile Application to Reduce Sedentary Behavior. *Personal and Ubiquitous Computing* 17, 6 (Aug. 2013), 1237–1246. https://doi.org/10.1007/s00779-012-0588-0

[77] E. G. Wilmot, C. L. Edwardson, F. A. Achana, M. J. Davies, T. Gorely, L. J. Gray, K. Khunti, T. Yates, and S. J H Biddle. 2012. Sedentary Time in Adults and the Association with Diabetes, Cardiovascular Disease and Death: Systematic Review and Meta-Analysis. *Diabetologia* 55, 11 (2012), 2895–2905. https://doi.org/10.1007/s00125-012-2677-z

[78] Fengpeng Yuan, Xianyi Gao, and Janne Lindqvist. 2017. How Busy Are You?: Predicting the Interruptibility Intensity of Mobile Users. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, 5346–5360. https://doi.org/10.1145/3025453.3025946

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