# Combating Sedentary Behavior: An App Based on a Distributed Prospective Memory Approach

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## Abstract
Sedentary behavior such as sitting is associated with severe health issues. We suggest that the sedentary behavior problem can be considered as a prospective memory task: remember to get enough activity within 30-minute periods. We describe the functions, development, and pilot evaluation of a theoretically motivated smartphone app to combat the sedentary behavior based on human movement research and distributed prospective memory. Finally, we outline the methods of a larger evaluation of the app and discuss limitations and future extensions of the distributed prospective memory approach.

## Author Keywords
Sedentary behavior; prospective memory.

## ACM Classification Keywords
H.5.2 Information interfaces and presentation (e.g., HCI): User Interfaces- Theory and methods

## Introduction
People spend a lot of time sitting: at work, commuting, watching television, etc. Such sedentary behavior is associated with, for example, an increased risk of diabetes, cardiovascular disease, and mortality [6].

Early on, HCI research suggested possible technologies to support individuals to become more active [e.g., 4]. However, the majority of technologies, and most of the commercial products, aimed at more exercise, such as going to the gym or walking for a set number of steps per day rather than reducing prolonged sitting times [for recent reviews of smartphone apps, see 3]. Notably, the sedentary behavior problem is a different issue and needs to be addressed separately. A more active lifestyle (e.g., regular exercise for 30 minutes a day) seems to not counteract the health-related negative effects of a sedentary lifestyle in moderately active populations [9]. Furthermore, only a few technologies [e.g., 15] based their functionality on the insights from human movement research, such as the acceptable sedentary duration, the length of physical activity during a break or the required energy expenditure during a sedentary break. Finally, research frequently considers behavior change as the ultimate aim of a technology-supported intervention [e.g., 18; 27]. Technology is considered to be a “temporary coach”, and the user learns new habits that persist even though the technology is not used anymore. However, the target behavior may return to its initial level when the technology is no longer used [18; 25].

In this paper, first, we characterize the sedentary behavior problem as prospective memory task. Second, we suggest a systems approach based on the idea of distributed cognition [17]–considering how agents (human and non-human) process information to achieve an aim–as an alternative solution to the sedentary behavior. Third, we describe the functions, development, and pilot evaluation of a smartphone app prototype that is following such a distributed cognition approach.

## Characterizing the Sedentary Behavior Problem as Prospective Memory Task

The physiology of prolonged sedentary behavior and its relationship to health outcomes has not yet been fully understood. One suspected biological mechanism is that through the absence of large muscle group contractions during sedentary behavior healthy fat metabolism is compromised, and the breakdown and use of glucose is reduced [14]. At present, research suggests a postural change every 20-30 minutes with brief bouts of activity [8]. The sedentary behavior should be interrupted by at least light-intensity physical activity (>1.5 Metabolic Equivalent of Task, MET) to achieve an energy expenditure of a minimum of 2-3 MET-minutes, such as walking for about 60 seconds.

The prototypical situation of prolonged sitting is office work. However, any activity with 1.0 - 1.5 MET is considered as sedentary behavior. The above recommendation should, therefore, be considered during office work, but also in leisure time. Therefore, the problem is pervasive in our everyday life and the context of sedentary behavior is changing frequently.

Sedentary phases are seldom the purpose of activity, such as leaning back in a comfortable chair and resting. Most of the time, we are sedentary and do something else. This other task requires our attention, such as writing a paper in the office. During sedentary behavior, our attention is frequently captured by a task-at-hand.

Based on the above analysis, we consider interrupting the sedentary behavior to be a prospective memory task. Prospective memory tasks are intentions that one needs to remember to do a specific task at a later point in time [7]. The focus of prospective memory research is not so much on what has to be done but rather *that* something has to be done at all. In the case of sedentary behavior, one needs to remember to get enough activity within 30-minute periods.

Prospective memory tasks are challenging. Particularly, if no external event or cue prompts the task (so-called event-based tasks, such as a post-it note) [7], then we must remember to perform the task after a specific time period elapsed (time-based tasks) [22]. Because the context of sedentary behavior is frequently changing, it is unlikely to have regular environmental cues. In addition, research suggests interrupting sedentary behavior at least every 30 minutes. Therefore, cues would need to be encountered at specific times and only if the sedentary behavior has been uninterrupted. Finally, if someone's attention is captured by an engaging task, such as writing a manuscript, cues may be detected less likely and particularly time-based prospective memory tasks are more prone to be forgotten.

### A Distributed Prospective Memory Approach

Frequently, researchers implicitly consider the problem that individuals do not get enough activity as a prospective memory task when they refer to providing "reminders" [e.g., 5; 23]. In the context of HCI supported habit formation, researchers have also considered prospective memory in light of forming new associations between existing routines and new behaviors [e.g., 27]. An essential component of habit formation is a stable context to create an association between a contextual cue and a task, which triggers an automatic action [19]. However, sedentary behavior is pervasive and, therefore, it will be difficult to find a specific cue or multiple cues to which activity can be associated. In addition, the most recent activity should be considered to determine whether an individual needs to get active at all.

Based on the cognitive systems engineering idea that technology and humans build a joint cognitive system to achieve a task [16], we suggest that we need an appropriate technology to compensate for the difficulties that humans encounter when intending to avoid prolonged sedentary activities. The idea of distributed prospective memory [13] suggests that parts of a prospective memory task can be externalized to technology. For the present problem, technology would need to remember when a sedentary behavior should be interrupted by considering the length of the sedentary activity but also possible energy expeditors that occurred as part of a specific activity. For example, when writing a manuscript one may get up to pick up a print job or pick up a book from the shelf. Essentially, the technology should only remind an individual to get active if not enough physical activity (i.e., at least >2 MET-minutes) has been recorded during a set period (i.e., 30 minutes).

This approach may seem provocative because previous research attempted to avoid sedentary activity by changing behavior permanently [e.g., 5] and HCI research on habit formation in general [e.g., 27]. An argument against a distributed prospective memory approach may be dependency on technology. If, however, the sedentary behavior problem is considered as a prospective memory task, this task is very difficult to remember. Instead of dependency, we suggest considering the term human-technology collaboration because, eventually, technology enables us to do things that are impossible without technology [16]. A further argument is that individuals may be prone to deskilling, such as losing the skill to plan and perform a prospective memory task on their own. Such a concern has been raised in the literature [e.g., 21] but we are not aware of any empirical evidence. Finally, in the case of fitness-related tracking, long-term use seems to have even motivational benefits for some users [11].

## Smartphone App Prototype

For the purpose of evaluating the approach, a smartphone app seemed appropriate. This technology does not require additional hardware, such as a sensor attached to the user's clothing, and is generally available.

*Functions*

The main functions of the app are (1) tracking of the activities sitting, standing, getting up, and walking, and (2) making the user aware of prolonged sitting times. If the app is started, a timer counts down from 30 minutes. The activities are tracked and if the user does more than 2 MET-minutes before the time runs out, the timer and the MET counter are reset. In addition, the user receives a notification (without haptic alert). If the time runs out (i.e., 30 minutes without enough physical activity), the user receives a notification (with haptic alert) to get active. If the user stays inactive, the haptic alert is repeated once before the timer and the MET counter are reset after 90 seconds. Finally, activity tracking was only conducted if the smartphone was in the pocket. The app provides further functions and settings that can be changed; however, these additional functions are not of interest for the present purpose.

*Development*

In order to be able to use the app on many smartphones, the app was developed on Android Version 4.0.3 (API-Level 15). To distinguish the four activities, we used the gyroscope and an existing step counter. In short, sitting was derived from a horizontal smartphone position, standing from a vertical smartphone positon, and getting up (or squatting) from a horizontal-vertical position change. Because tracking the activities was based on the gyroscope, we needed to ensure that no tracking occurs if the smartphone is not in the pocket. For example, in the case of an upright position, the app would have otherwise logged standing. To this end, the app only logged data if the light sensor registered an illuminance <5 Lux.

After an initial test phase, we developed a test protocol, and five participants completed the protocol. The experimenter used a stop watch to measure the length of several activities that the user had to do such as getting up, walking to a chair, sitting down etc. We used 1-second units to determine the agreement between the app and the experimenter. The mean Cohen's Kappa was 0.76 (SD=0.07). The mean difference in step count was 2.6 (SD=2.4). The app detected 87% of all steps. We concluded that the accuracy was sufficient for the present purposes.

In the pilot, we chose the very minimum of 2 MET-minutes per 30-minute period. To determine how much activity is required to achieve 2 MET-minutes, we assigned MET scores to the different activities based on the literature. Because standing is frequently associated with an additional activity rather than standing quietly, we assigned 1.8 MET [20]. Walking was assigned 3.5 MET [1]. Getting up was assigned the

**Pilot Evaluation**

**Participants:** Convenience sample of five participants (mean age 23 years; all male; 2 students, 2 clerks, 1 apprentice). The app was installed on the participants' smartphones (five different Android versions).

**Procedure**: The activity was tracked for five days during working periods only:

- On the first day, the smartphone only logged activity (baseline).
- On two days, the app worked as described in the text (app).
- On two days, the smartphone notified (with haptic alert) participants every 30 minutes to do some activity if the MET-minute score was <2 or informed (no haptic alert) participants that enough activity has been done in the past 30 minutes (static reminder).

The order of app and static reminder was counter balanced.

value of squatting for one second (8.07 MET) [2]. Every second, the app multiplied the time of an activity by the respective MET value to calculate the energy expenditure in MET-seconds. For example, getting up (1 second of 8.07 MET) + standing for 20 seconds (20 × 1.8 MET) + walking for 25 seconds (25 × 3.5 MET) would result in 132 MET-seconds.

*Pilot evaluation*

The aim of the study was to pilot a larger evaluation of the app and to get initial data on (1) sedentary behavior, (2) MET values, (3) sedentary behavior time until >2 MET (4) number of notifications to get active, (5) percentage of compliance to notifications, and (6) the number of notifications for enough physical activity (i.e., >2 MET). We compared the app to a baseline (only activity logging) and a static reminder condition (reminder every 30 minutes, see box Pilot Evaluation). Participants answered a questionnaire at the end of the static reminder and app condition (Table 2).

The results showed significant differences for sedentary activity and average MET values (Table 3). Bonferroni-corrected post-hoc tests showed that participants were sitting less (p=.034) and were more active (p=.002) with the app compared to the baseline, only. In all conditions, participants frequently spent too long in sedentary behavior. Considering the notifications to do some activity, participants received a notification about every second 30-minute period, with no differences between conditions. Compliance in both conditions to get active in the 90 seconds after the reminder was 14% on average only. Finally, participants received more (positive) notifications that a MET score of >2-minutes was accomplished in app than in the static reminder condition.

The participants have been more active in the app than in the static reminder condition. However, if this was because of reminding the participant to get activity, compliance to the notification should have been higher for the app than the static reminder condition. One may conclude that more notifications of enough activity may have acted as a positive reinforcement, but many notifications in the app condition may have also resulted in low compliance to the notifications to

| | Base-line | Static reminder | App | p-value |
|---|---|---|---|---|
| Sedentary behavior in min per 30 min | 28.9 (28.8-29.1) | 28.8 (28.8-29.0) | 28.3 (27.0-28.9) | .022 |
| MET-seconds values per 30 min | 167.2 (123.1-172.3) | 193.5 (186.3-194.2) | 239.7 (199.9-382.3) | .007 |
| Sedentary behavior in min until >2 MET | 43.3 (41.9-58.6) | -* | 35.6 (20.4-50.4) | .655 |
| Notifications to get active per 30 min | - | 0.49 (0.46-0.60) | 0.47 (0.18-0.59) | .655 |
| Percentage of compliance to notifications | - | 13.3 (6.7-23.1) | 15.3 (7.7-33.3) | .655 |
| Notifications for activity of >2MET per 30 min | - | 0.49 (0.37-0.52) | 0.75 (0.53-1.43) | .025 |

**Table 3**: Quantitative results of evaluation. Values represent medians (min-max). P-values of Friedman tests. *could not be calculated because app logged data only every 30 minutes

| | Static | App |
|---|---|---|
| I liked this technology. | 5 (5-6) | 6 (5-7) |
| The technology was conspicuous. | 4 (3-6) | 3 (2-4) |
| The technology was disrupting. | 4 (5-7) | 3 (2-4) |
| The technology was motivating. | 6 (5-7) | 6 (5-6) |
| The technology made me more active. | 5 (4-6) | 5 (4-6) |
| I would use the technology every day. | 5 (3-6) | 6 (4-6) |
| How many of the notifications (in %) did you follow? | 80 (70-90) | 90 (90-100) |

**Table 1**: Data of questionnaire after the end of 2-day use period. Values represent medians (min-max). 1 =strong disagreement; 7 = strong agreement. All Wilcoxon Signed Rank Tests were nonsignificant (p-values >.05)

become active. Finally, the difference between 85% subjective (Table 2) vs. 14% objective compliance rate (Table 3) highlights the need for objective activity tracking measures. Overall, the results need to be interpreted carefully because of the low number of participants and a short data-collection period.

## Discussion

We presented a theoretically motivated app to combat sedentary behavior based on insights from human movement research and distributed prospective memory. In short, we suggested that prolonged sitting times are a result of prospective memory failures and providing the respective technological support will reduce prolonged sedentary behavior.

The app did work without problems, and we think that the variables will enable interesting insights for sedentary behavior research. In a next step, we plan a larger evaluation of the app. If participants comply with the notifications, the sedentary behavior problem may be indeed considered as a prospective memory problem. In addition, we need to investigate how the users actually use the app and experience using the app over a longer period [11; 12; 25]. Qualitative data are important to gain insights on usability and user experience, how the app changed the users' perception of the sedentary behavior problem, and reasons for long-term adoption of the app. Furthermore, the qualitative data can be analyzed to further investigate whether the sedentary behavior problem is a prospective memory problem or whether the presented approach is too limited.

A limitation of the app is a missing motivational component. Users with more motivation to avoid prolonged sedentary behavior (i.e., other than the *precontemplation* stage on Prochaska and Velicer's stage of change questionnaire [24]) may already benefit from the current version but users low in motivation may need a more pervasively designed app or a gamification component. In terms of Fogg's behavior model [10], at present, the app provides (signal) triggers but no motivation or ability.

A technical limitation is that the user has to keep the smartphone in the pocket. This may be especially problematic for women. A solution might be a small clip-on device that can track sedentary and other activities and send notifications in combination with a smartphone app to change settings. Future studies should pay more attention to this issue and consider gender-balanced samples. Furthermore, considering human movement research, the very low threshold of 2 MET-minutes can also be considered as a limitation.

Finally, one may consider that the app has only a reminder function as a limitation [25; 26]. A further development of the app may also include an algorithm that reminds the user to get active if a specific environmental cue appears. For example, in the case of an incoming phone call or a when attempting to make a phone call, the app could send a notification that the user should stand while being on the phone. The user may learn to get active for specific tasks.

In conclusion, distributed prospective memory may provide a fruitful approach to avoid prolonged sedentary behavior. Future research should also investigate the benefits of combining different HCI theories to combat the sedentary behavior and prevent severe health issues.

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