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SedVis: Supporting Sedentary Behavior Change by Visualizing Personal Mobility Patterns and Action Planning on Smartphone

Abstract
Background: Prolonged sedentary behavior is related to a number of risk factors for chronic diseases. Given the high prevalence of sedentary behavior in daily life, light-weight solutions for behavior change are needed to avoid detrimental health effects.

Objective: The mobile app SedVis was developed based on the Health Action Process Approach. The app provides personal mobility pattern visualization (for both physical activity and sedentary behavior) and action planning for sedentary behavior change. The primary aim of the study was to investigate the effect of mobility visualization on users' action planning for changing their sedentary behavior. The secondary aim was to evaluate user engagement with the visualization and user experience of the app.

Methods: A three-week pilot study was conducted with 16 participants who had the motivation to reduce their sedentary behavior. A mixed study design (with one between-subject factor and one within-subject factor) was adopted. In the one-week baseline period, both the active control group (N=8) and the intervention group (N=8) had no access to the functions in the app. In the following two-week intervention period, only the intervention group was given access to the visualizations, while both groups were asked to make action plans every day and reduce their sedentary behavior. Participants' sedentary behavior was estimated based on the sensor data of their smartphones, while their action plans and interaction with the app were also recorded by the app. Participants’ intention to change their sedentary behavior and user experience of the app were assessed using questionnaires.

Results: The data were analyzed using both traditional null-hypothesis significance testing and Bayesian statistics. The results showed that the visualizations in SedVis had no statistically significant effect on the participants' action planning. The intervention involving the visualizations and action planning in SedVis had a
positive effect on reducing participants’ sedentary hours with weak evidence (mean -0.40, SD 0.63), while the active control condition did not decrease sedentary time (mean 0.17, SD 1.65). The results also suggested that the more frequently the users checked the app, the more they might reduce their sedentary behavior; however, this finding did not reach statistical significance. The visualizations in the app also led to higher user-perceived novelty. No participant complained about the interruption, while some participants commented that making action plans every day was boring.

Conclusions: Using a smartphone app to collect mobility data and provide feedback in real-time using visualizations might be a promising method to induce changes in sedentary behavior and might be more effective than action planning alone.

Keywords: Sedentary Behavior Change; Data Visualization; Mobile Application; Action Planning; Mobility Pattern.

Introduction

Background
Sedentary behavior refers to any waking behavior characterized by an energy expenditure ≤1.5 metabolic equivalents (METs) while in a sitting, reclining, or lying posture [1,2]. Studies have shown evidence of the detrimental effects of prolonged sedentary behavior, which is ubiquitous in daily life, especially when at work. For instance, a study [3] tracking 425 adults for about ten years (2002–2004 to 2012-2014) showed that greater increase in sedentary behavior was associated with detrimental changes in cardiometabolic risk factors, such as waist circumference, high-density lipoprotein cholesterol, and triglycerides, independently of the change in moderate-to-vigorous physical activity. In other words, exercise after sitting much during work time might not reduce the health risk caused by prolonged sitting. Moreover, a study [4] involving 168 participants in Australia showed that the total number of breaks in sedentary time was associated with improved health parameters, such as significantly lower waist circumference, BMI, triglycerides, and 2-h plasma glucose. Consequently, several governments (e.g., Australia1 and Canada2) have released guidelines to specifically reduce people’s sedentary behavior for improved health. For example, people with sedentary lifestyle could introduce light physical activity (e.g., short walking) throughout the day to reduce the risk of many chronic diseases.

The high prevalence of opportunities to be sedentary in daily life leads to high habit strength of sedentary behavior [5], i.e., a high degree of automaticity due to frequent repetition in a stable context [6], which makes it difficult to change in the long term [7]. Interventions are therefore needed to support individuals to reduce their sedentary time. In their review, Chu et al. [8] divided intervention strategies for reducing sedentary behavior to three categories: (1) educational/behavioral (e.g.,

1 http://www.health.gov.au/internet/main/publishing.nsf/Content/health-pubhlth-strateg-phys-act-guidelines
2 https://csepguidelines.ca/
goal setting, action planning, and self-monitoring); (2) environmental changes (e.g., sit-stand workstation and treadmill desk); (3) multi-component (e.g., sit-stand workstation plus goal-setting). The environmental and multi-component interventions might require policy support and additional facilities, which might hinder their immediate application on a larger scale. Therefore, low-cost and light-weight solutions are needed.

Mobile devices, including smartphones and wearables (e.g., smartwatches and fitness wristbands), might be useful platforms for sedentary behavior interventions. Firstly, the prevalence of both smartphone and wearable device ownership is increasing globally [9]. As smartphones include sensors that allow for the collection of physical activity data [10], smartphone owners do not need additional devices to collect data and receive interventions, thus making the solution light-weight. Secondly, interest in mobile apps targeting lifestyle behaviors such as physical (in-)activity is high (e.g., [11]). Accordingly, research on digital solutions for the promotion of physical activity and the reduction of sedentary behavior is increasing [12]. However, compared to the number of apps targeting physical activity, there are only a few apps specifically targeting sedentary behavior [13]. Moreover, as previous reviews noted, both commercially available apps and apps developed for research are often not grounded in theory, which might limit their effectiveness [14]. The present research, therefore, sought to develop a mobile application for sedentary behavior change that is grounded in behavioral theory.

**Action Planning for Sedentary Behavior Change**

Wang et al. [15] recently proposed a holistic framework for developing digital health behavior interventions, drawing from several classic theories of health behavior change in psychology such as social-cognitive theory [16,17] and the Health Action Process Approach (HAPA; see also Figure 1; [18]). The latter theory is especially important for the design of health behavior interventions as it bridges the intention–behavior gap through action planning [19]. Indeed, several meta-analyses have shown that action planning was positively related to goal attainment and health behavior change (e.g., [20–22]) and thus might be an effective behavior change technique. Accordingly, action planning was included in the taxonomy of behavior change techniques [23]. An action plan combines specific situation parameters (“when” and “where”) and a sequence of actions (“how”) for a target behavior [18]. In this vein, it is suggested that behavior will be triggered automatically when encountering specific situations [24].
Although action planning is an effective behavior change technique, there are only a few studies that included action planning in digital interventions targeting sedentary behavior [25]. In a recent systematic review of digital technologies supporting health behavior change [26], only two out of 45 reviewed studies involved action planning related to sedentary behavior change. Based on step counts at baseline, Aittasalo et al. [27] offered the participants visual feedback to facilitate their action planning, while De Cocker et al. [28] used several motivational questions to stimulate the participants to make action plans. In both studies, sedentary behavior was successfully reduced. However, both used action planning as one of several behavior change techniques, and it is, therefore, unclear whether the change can be solely attributed to action planning. Maher and Conroy [5], on the other hand, specifically tested the main effect of action planning on reducing sedentary behavior and found that daily action planning did not induce sedentary behavior change. This study, however, has limitations. First, sedentary behavior was only assessed subjectively, which might not correspond to objectively measured behavior [29]. Second, the quality of the action plans was not evaluated. This, however, might have provided important insights into why the intervention was not successful.

The quality of an action plan can be evaluated based on plan characteristics such as specificity of the situational parameters, plan instrumentality, i.e., the degree to which a plan is helpful to achieve the desired outcome, and viability, i.e., how realistic an action plan is. Fleig et al. [30] showed that specificity of when to perform a behavior and instrumentality of the action plan were related to an increased likelihood of plan enactment. Quality of action plans, therefore, might be an important variable to consider when evaluating interventions. While none of the aforementioned studies on sedentary behavior change investigated the quality of action plans, the present study aimed at testing the effect of action planning on sedentary behavior change quantitatively and additionally included a qualitative analysis of the action plans to determine their specificity, instrumentality, and viability.
Visualizations of Mobility Patterns

Mobile devices allow for the passive monitoring of physical activity and sedentary behavior. When fed back to the user, the data might help them to generate meaningful insights about their activity patterns and subsequently induce behavior change. Self-monitoring and feedback based on the collected data are frequently used to change physical activity and sedentary behavior [31–34]. However, the feedback is often numerical or uses simple static visualizations such as bar charts or line graphs to display step counts or energy expenditure (see, e.g., Google Fit, Fitbit). Based on this information, it might be difficult to extract all relevant information needed to formulate effective action plans defining the “when,” “where,” and “how.” It could be hypothesized that map-based visualizations, such as visualizations provided by apps to track running, might be more effective, as they provide information about where activities took place [35].

Building upon the idea of that visualizations of sedentary behavior data might facilitate action planning (see also Aittasalo et al. [27]), a novel tool to support action planning for reducing sedentary behavior using interactive visualization was developed. The present study thus extends previous mobile sedentary behavior interventions by using an interactive visualization of sedentary behavior data to specifically support daily action planning, which in turn was hypothesized to reduce sedentary time in daily life. A mobile app – SedVis – was implemented by the study team. Mobility patterns were determined based on objective data collected by the app: Using internal sensors of the smartphone and existing services provided by the operating system, SedVis automatically tracks and classifies users' activity (e.g., walking, biking, and being in a vehicle), steps count, and locations, and in this vein determines locations and time windows in which users are sedentary. The visualization elements thus correspond to the aforementioned action planning factors - when, where, and how (i.e., the planned activity). Through specifically highlighting situations in which users are sedentary, the visualizations can serve as a visual aid for formulating action plans. To the best of our knowledge, SedVis is the first app targeting visualizations and action planning on mobile devices for sedentary behavior change.

Study Objectives

This paper reports on the results of a three-week pilot study of SedVis (N=16), which was a first usability and feasibility test of the app. Specifically, the study aimed to answer four research questions (RQ). The first aim was to examine the effect of SedVis on users’ action planning for their sedentary behavior change (RQ1). Specifically, it was tested whether using the visualization improved three characteristics of action plans which have been identified as potentially impacting effectivity of the plans for behavior change [30]: (1) specificity, i.e., the level of detail the plan provided on when and where the behavior was to be shown, (2) instrumentality, i.e., the degree of the helpfulness of the plan for behavior change, and (3) viability, i.e., the degree of control an individual has over plan enactment, of formulated action plans were studied. Second, it was tested whether the intervention involving visualizations and action planning is effective in reducing
sedentary behavior compared to action planning without visualizations (RQ2). Third, because the designed visualizations could also serve as a self-monitoring tool, users’ engagement with the visualizations in SedVis and its impact on users’ sedentary behavior change was investigated (RQ3). Four, user acceptance and experience of SedVis as a light-weight intervention tool for the daily use of the sedentary population were studied (RQ4).

Methods

SedVis App

Data Collection

SedVis was developed for Android smartphones and pre-tested internally by the study authors. It collected the data of physical activities (via Google Activity Recognition API3), geolocation (via Google Maps API), steps (via Google Fit API), screen states (turned on or off), users’ interaction within the app, users’ action plans, and time stamps. Based on the build-in sensors’ data, Google Activity Recognition service in Android platform could recognize physical activities including running, walking, cycling, being in a vehicle, and being still. As high battery consumption (e.g., through constant geolocation tracking) or large disk-space requirement might lead to users’ abandonment of the app, geolocation was only updated when movements were detected based on activity recognition and steps counting every five seconds. Besides, a new data point was only recorded when a change of the activity state was detected (e.g., the steps increase or the physical activity changes). This strategy minimizes energy consumption and data storage without losing information on users’ mobility [36].

To improve power consumption, Google imposes limitations on background services since Android 8.04. Some OEM versions (e.g., MIUI5 and EMUI6) of Android additionally introduced limitations on background services to optimize the battery life. The operating system might kill the background service automatically. Therefore, the logged data might not tell the difference between true sedentary periods and the periods during which the background service was not running. Therefore, a timer was added to the background service to log a timestamp to the local database every 20 minutes. To improve the data collection quality, data collection service was bound to a notification showing the latest update time, steps, and activity in the notification bar (as shown in Figure 2). A system clock was used to monitor if the background service is running and, if necessary, to initiate a restart. Users could also manually re-start the data collection service if the notification disappeared.

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3 https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognitionClient

4 https://developer.android.com/about/versions/oreo/background

5 https://en.miui.com/

6 https://consumer.huawei.com/en/emui/
Mobility Pattern Detection

Mobility patterns refer to when, where, and how the user moves/is sedentary, which directly correspond to the three elements in action planning (i.e., when, where, and how). In SedVis, this involved tracking of users’ moving trajectory and sedentary place detection. The trajectories showed the routes the user had taken and related information on step counts and time windows. The app detected the users’ physical activity every five seconds, which enabled a high temporal resolution for trajectory tracking. Modern smartphones use high-precision and low-power movement sensors, which makes the physical activity recognition and steps tracking both accurate and efficient [37]. Google Play services provide fused location tracking by using GPS, Wi-Fi, and cellular signals to allows for precise positioning even in some indoor environments\(^7\).

Custom programmed sedentary place detection was used to detect the participants’ sedentary places based on the users’ geolocation data. Many office workers spend the day in a limited number of locations (e.g., home, office, lab) where they spend much time sitting. Existing services, like the Places SDK for Android\(^8\), only provide public places (e.g., the university), which could not enable personalized place detection in other places such as at home. Therefore, a spatio-temporal data clustering algorithm [38] was used to detect the places based on each user’s data. These detected sedentary places provide users intuitive cues on where to reduce their sedentary behavior, which were displayed in mobility pattern visualizations.

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\(^7\) Accuracy depends on the strength of the indoor Wi-Fi and cellular signals.

\(^8\) [https://developers.google.com/places/android-sdk/intro](https://developers.google.com/places/android-sdk/intro)
**Mobility Pattern Visualization**

Within SedVis, users could access two visualizations of data on their sedentary and active hours that were generated based on the collected mobility pattern data. An hour was labeled sedentary if the user took fewer than 250 steps/hour as in the Fitbit mobile application\(^9\) and according to recent evidence suggesting that two-minute walking (about 250 steps) per hour might lower the risk of premature death [39].

Participants could access the single-day visualization via the dashboard or by clicking the always-on notification (see **Figure 2**). In the daily visualization, the tracked trajectories and the detected sedentary places were shown on a map, and the corresponding temporal information was shown using a bar chart (as shown in **Figure 3**) for a single day. Specifically, sedentary hours were marked by orange bars, and sedentary locations were marked with orange triangles on a map to highlight situations in which users were sedentary. Participants could interact with the visualization by tapping on the bar chart or on the locations and trajectories displayed on the map. Specifically, they could see (1) the active hour(s) and the corresponding routes on the map once clicking on a blue bar, and (2) the sedentary hour(s) and the corresponding locations once clicking on an orange bar. Likewise, clicking the sedentary location on the map highlighted the corresponding sedentary hours in the bar chart. While the bar chart illustrated temporal patterns, the map demonstrated spatial patterns. Participants could switch between days by tapping on the arrows at the bottom of the screen.

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\(^9\) [https://www.fitbit.com/app](https://www.fitbit.com/app)
In the multi-day visualization, data were aggregated across multiple study days. Sedentary places were determined based on aggregated data from the user-selected days. Differing from the daily visualization, the bar chart in the multi-day visualization showed the frequencies the user was sedentary in each hour during the selected days for all the places or one selected place (see Figure 4).

Figure 3. The mobility patterns in the daily visualization mode.

Figure 4. The multi-day visualization.
**Action Planning**

The user could enter the action planning view from the dashboard, the daily notification, or the shortcuts in the visualization views (see the second button in the left-up corner of Figure 3 and Figure 4). All action plans that the user had made were shown in a list view. The action plans were shown chronologically and could not be deleted. When adding an action plan, the user was asked to specify the “when,” “where,” and “how” elements (see Figure 5).

![Figure 5. The action planning function in the app.](image)

**Dashboard**

From the dashboard of SedVis, participants could access all the functionalities of the app, as shown in Figure 6. In the settings tab, the study staff could enable intervention functions. Passwords were used to restrict the users’ access to these functions during the study.
Figure 6. The dashboard of SedVis.

Study Design and Procedure

The study deployed a mixed design with one between-subject factor Group (with vs. without visualization) and one within-subject factor Time (baseline vs. intervention) (see Figure 7). Participants were assigned to one of two groups, which determined the intervention they received: Group A (intervention group), for which the visualization functions were enabled; Group B (active control group), for which the visualization functions were disabled. Participants were assigned to the groups according to the enrollment time (i.e., every odd number was assigned to Group A, while every even number was assigned to Group B). This strategy enables fast study-deployment for each participant while keeping the balance of sample size in both groups [40]. To some extent, this strategy also preserved randomization.

The study included three interviews (i.e., the entry interview before starting data collection, the after-baseline interview after week 1, and the exit interview after week 3) on day 1, day 9, and day 25 for each participant. The data collected on these three days in the app were excluded in data analysis as it was incomplete and could not be compared between participants due to appointments being scheduled throughout the day.
During the entry interview, the participants were informed about the purpose of the study, signed the consent form, and filled out questionnaires on demographics and psychosocial variables related to sedentary behavior (intention, risk perception, self-efficacy based on the Health Action Process Approach [18]10). A member of the study staff then installed SedVis on their smartphones.

The after-baseline interview took place on the first day after the baseline week. Participants again filled out the questionnaire on psychosocial variables before watching an educational video about the risks of prolonged sedentary behavior11. Subsequently, the study staff showed them a flyer to explain a behavior change theory [41] and emphasized the importance of action planning. The participants were asked to make at least one plan per day to reduce their sedentary behavior for the following two weeks. Finally, the study staff introduced the functions in the app, depending on which group participants of the session were assigned to. For Group A, all the functions were activated, including daily visualization, multi-day visualization, which allowed for displaying mobility patterns for multiple days, and action planning. For Group B, only the action planning function was enabled. Participants were demonstrated how to make an action plan in the app with dummy examples (e.g., “10 am, office, take a walk”). For both groups, participants were asked to set a daily reminder within the settings of the app when they used it for the first time, which served as a prompt to make action plans.

After two more weeks, the participants returned to the lab for the exit interview, when they again completed a questionnaire on psychosocial variables as well as an additional questionnaire on user experience. They furthermore transferred the data stored on their smartphones to the study team by email and took part in a short semi-structured interview. Participants were asked questions about their current health status, especially regarding acute infections that might have limited their physical activity, changes in daily routines that might have affected their physical activity or sedentary behavior, and divergences from their sleeping habits, e.g., having slept longer or shorter than usual. In addition, they were provided with a list of their action plans and asked to rate them. The participants’ answers were written on printed forms and archived into the digital forms after the study. Each participant received 20€ after completing the study.

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10 Only results for intention are reported as it is the only construct directly associated with action planning.

11 https://youtu.be/wUIel8KmMz4
The ethics committee of the University of Konstanz approved the study protocol. For privacy reasons, only data related to the study was collected. To ensure transparency of data collection, data was recorded and stored on the participants’ smartphones until the study was finished. The participants were showed the data details when they transferred the data via email to the study staff. The data remained anonymous and stored on the encrypted server hosted in the university.

**Participants**

Participants were recruited through university mailing lists, the authors’ social media profiles, and posters in the university. Sixteen participants expressed interest in taking part in the study. Participants were eligible for participation if they (1) had the intention to change their sedentary behavior; (2) had no injuries that precluded them from being physically active; (3) were able to speak English fluently; (4) owned a smartphone with Android 6.0 and above; (5) did not use a standing desk; (6) had no travel plans during the study period. The fifth criterion was used to filter out people who already started to change their sedentary behavior. The other criteria were used to control the motivation and objective ability for using the app, communicating with the study staff, and changing sedentary behavior. The criteria were listed in the study advertisement, and potential participants self-evaluated whether they fit the inclusion criteria. In addition, the intention to change sedentary behavior was assessed in the entry interview as a control measure.

All participants were students (9 PhD students; 9 females) at the university. Group A comprised of five females and three males. Their mean age was 26.6 years (standard deviation (SD) 3.8). Group B comprised four females and four males. Their mean age was 27.0 (SD 4.0). Among the 16 participants, one was overweight (i.e., BMI > 25 kg/m²), one was underweight (i.e., BMI < 18.5 kg/m²), and the remaining had a normal weight (BMI mean 22.0 kg/m², SD 2.8).

**Measures**

**Sedentary behavior**

Sedentary hours were assessed throughout the three weeks of the study and calculated based on the steps counts assessed by the SedVis app, which were again determined based on the Google Activity Recognition API native to Android smartphones. Studies have shown that off-the-shelf smartphones and smartwatches could provide a reliable estimation of users’ physical activity (e.g., [37,42]). Sedentary behavior was quantified per hour: An hour was labeled as sedentary if less than 250 steps were recorded.

It should be noted that the sedentary hours the app estimated included the participants’ sleeping time. It was assumed that the participants’ sleeping time did not change over the three-week study, which was confirmed by the participants in the exit interview. Thus, the difference in the daily sedentary hours between the baseline week and intervention weeks should not be influenced by the sleeping
hours. The estimated sedentary hours will be used to reflect the sedentary behavior in the rest of the paper.

**Number of action plans**
The total number of action plans formulated during the two-week intervention phase was counted automatically by the SedVis app. Since participants were allowed to repeat the plans of previous days, the number of unique action plans was calculated additionally.

**Quality of action plans**
To evaluate the quality of the action plans, the specificity of the When, Where, and How of the plans were coded. The rating criteria for three levels of specificity (i.e., vague, medium specific, and highly specific) were adapted from Fleig et al. [30] (see Table 1 for coding criteria). In addition, participants were asked to evaluate the viability (how realistic) and instrumentality (how useful) of their action plans based on the plan characteristics used by Fleig et al. [30]. For viability, participants were asked to rate each action plan on a scale from 1 (not realistic at all) to 4 (very realistic); for instrumentality, participants were asked to rate each action plan on a scale from 1 (not helpful at all) to 4 (very helpful).

**Table 1. Coding criteria for specificity.**

|          | Vague (=1)                              | Medium Specific (=2)                  | Highly Specific (=3)               |
|----------|-----------------------------------------|--------------------------------------|-----------------------------------|
| **“When”** | Empty; “Now”; “Anytime”; “Today”   | “Every Hour”; “After Lunch”           | Timepoint (e.g., “13:00”)         |
| **“Where”** | Empty; “Out”                     | Large area (e.g., “City,” “University”) | Places (e.g., “Post,” “Lab,” “Office,” “Home,” “Library”) |
| **“How”**   | Empty;                               | “Going to the park”                   | Activity (e.g., “Walk,” “Yoga,” “Cycle,” “Pushups,” “Stretch,” “Stand up”) |

**Engagement with the app**
Participants’ interaction with the app was quantified by recording all operations in the app during the study, including how often the participants checked the visualizations. In addition, timestamps of when participants made action plans were logged, which were then used as the basis for discussing the users’ experience with the app during the exit interview.

**Intention to change sedentary behavior**
The participants’ intention was measured using a scale from 1 (I do not plan to reduce my sedentary behavior at all true) to 4 (I do exactly plan to reduce my sedentary behavior) following the example in HAPA [18]. The intention was used as a control measure as participants were required to be motivated to reduce their sedentary behavior instead of other factors (e.g., receiving monetary compensation).
**User experience**

Using the user experience questionnaire (UEQ) [43], the user experience of the app was quantified at the exit interview. In addition, open-ended questions were used to explore the participants’ attitudes to the app and the study, as well as their desired features missing in the app.

**Statistical Analysis**

Data were analyzed using both traditional null-hypothesis significance testing (i.e., t-tests, ANOVAs, and Pearson’s correlation coefficient) and equivalent Bayesian statistics to provide Bayes factors. In addition, descriptive statistics (means, standard deviations) are reported. RQ1 was evaluated by using (Bayesian) independent samples t-tests with the independent variable group and dependent variables total and unique number of action plans and measures of action plan quality. RQ2 was evaluated using a 2 Group x 2 Time mixed ANOVA using sedentary hours as the dependent variable. Bayesian paired samples t-tests were also used to investigate the change of sedentary hours in each group. RQ3 was evaluated using (Bayesian) Pearson correlations to examine the relationship between the frequency of checking the visualization and the sedentary hours. RQ4 was evaluated using (Bayesian) independent samples t-tests with the independent variable group and the UEQ scores as dependent variables. For all null-hypothesis significance tests, respective assumptions were checked, and no violations were identified.

The conventional null-hypothesis significance tests provide little information when the result is not statistically significant – only the alternative hypothesis is tested [44]. Non-significant results might support a null hypothesis over the alternative, or the data are just insensitive. By contrast, Bayes factors [45] compare the extent to which the samples support two hypotheses (e.g., equal or different). Besides, Bayesian methods also allow more principled conclusions from small-n studies of novel techniques in the field of human-computer interaction [46]. Therefore, Bayes factor (BF) was used in addition to the p-value [47] and Cohen’s d [48] to report and interpret the results. JASP12 (Version 0.9.2) was used for data analysis due to its ability to compute both the conventional null-hypothesis significance test and the corresponding Bayesian analysis.

The Bayes factor is a ratio of the likelihood probabilities. \( P(data \mid H_0) \) is the probability of the null hypothesis \( (H_0) \) given the data, while \( P(data \mid H_1) \) is the probability of the alternative hypothesis \( (H_1) \) given the data. The definition of the Bayes factor is shown in Formula 1 below.

\[
BF_{01} = \frac{P(data \mid H_0)}{P(data \mid H_1)} = \frac{P(H_0 \mid data)}{P(H_1 \mid data)} \times \frac{P(H_1)}{P(H_0)} \text{ or } BF_{10} = \frac{1}{BF_{01}} \tag{1}
\]

The Bayes factor indicates which hypothesis is more supported by the data. **Figure 8** shows the Bayes factor classification and the adapted interpretation [49]. The

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12 https://jasp-stats.org/
default priors of the alternative hypothesis and the calculation methods for different study designs can be found in the work of Rouder and colleagues [50,51].

![Figure 8. A graphical representation of a Bayes factor classification and the interpretation, adapted from [49].](image)

The default Cauchy distribution \( r = 1/\sqrt{2} \) was used as the prior when estimating the effect size. Following the JASP guidelines [49], also the median (M) and the 95% credible interval (CI) of the effect size are reported. For correlation analysis, the Bayesian Pearson correlation test was used with default prior suggested by Rouder and Morey [52]. Depending on the context, the one-side Bayes factor (BF0 or BF+0) or the two-side Bayes factor (BF01) are reported.

**Results**

**Data Collection**

All participants completed the study. First, data quality was checked based on the actual running duration of the app to ensure that all participants had access to the app as expected. The missing duration may be caused by the smartphone being switched off or the background service being shut down for battery optimization. Only the data from one participant in Group A (A8) showed a relatively low coverage (65.61% of the study duration); for the other participants, the mean coverage was 93.88% (SD 5.44%). After checking the data of participant A8, it was found that they had the habit of shutting down the phone during the night. Therefore, the missing data does not limit conclusions about the mobility of the participant, and the participant’s data was analyzed as planned.

**Participants’ Intention (Control Measure)**

The participants’ intention of reducing sedentary behavior was generally high (mean 3.20, SD 0.59) in both groups. No significant difference was found between groups at each appointment according to t-tests (appointment 1: \( t_{14} = 0.00, P = 1 \), Cohen \( d = 0.00 \); appointment 2: \( t_{14} = -0.37, P = .72, Cohen \( d = -0.19 \); appointment 3: \( t_{14} = 0.00, P = 1, Cohen \( d = 0.00 \)). The Bayes Factors showed evidence preferring \( H_0 \) (appointment 1: BF\(_{01} = 2.34 \); appointment 2: BF\(_{01} = 2.23 \); appointment 3: BF\(_{01} = 2.34 \)). The result indicated that the participants in both groups had similarly strong intentions.

**RQ1: Effect of Visualization on Participants’ Action Planning**

The first aim was to investigate the effect of the visualizations on participants’ action planning. Both the quantity and quality of the action plans were evaluated.
An independent samples t-test showed no significant group difference regarding the total number of action plans made in the two groups ($t_{14} = 0.36, P = .72$, Cohen $d = 0.18$; mean$_{Group\ A}$ 8.88, SD$_{Group\ A}$ 5.69; mean$_{Group\ B}$ 7.75, SD$_{Group\ B}$ 6.76). The Bayes factor (BF$_{01} = 2.24$, $M = 0.11$, CI [-0.66, 0.92]) showed weak evidence towards no difference (H$_0$). It was the same case for the number of unique action plans ($t_{14} = 0.88$, $P = .40$, Cohen $d = 0.44$, BF$_{01} = 1.81$, $M = 0.28$, CI [-0.50, 1.14]): the mean in Group A was 3.75 (SD 2.19); the mean in Group B was 2.75 (SD 2.38).

The quality of the action plans showed mixed results, as shown in Table 2. The means of the perceived viability and instrumentality are slightly higher in Group B than in Group A; however, again, t-tests showed no significant differences. The Bayes factor showed weak evidence towards difference (H$_1$) for the perceived viability, while it suggested no difference (H$_0$) for the perceived instrumentality. Also, no meaningful group differences were found regarding specificity (“When” and “Where”) according to t-tests and the Bayes factor, which indicated weak evidence supporting no difference (H$_0$). The means of the specificity of the response activity (“How”) were both very high in the two groups because most of the users simply specified the activity as walking.

Table 2. The measurements of the quality of the action plans.

|                      | Group A | Group B | $t_{14}$ | $P$  | Cohen $d$ | BF$_{01}$ | $M$  | CI        |
|----------------------|---------|---------|----------|------|-----------|-----------|------|----------|
| Perceived Viability  | 3.28 (0.68) | 3.81 (0.37) | -1.96 | .071 | -0.98 | 0.71 | -0.67 | [-1.72, 0.17] |
| Perceived Instrumentality | 3.10 (0.55) | 3.22 (0.73) | -0.52 | .608 | -0.26 | 2.13 | -0.15 | [-1.00, 0.59] |
| Specificity (When)   | 2.55 (0.70) | 1.88 (1.00) | 1.59 | .14 | 0.79 | 1.05 | 0.51 | [-0.30, 1.50] |
| Specificity (Where)   | 2.21 (0.82) | 2.10 (0.91) | 0.35 | .73 | 0.17 | 2.24 | 0.10 | [-0.68, 0.94] |
| Specificity (How)     | 2.99 (0.04) | 3.00 (0.00) | - | - | - | - | - | - |

Note. For Specificity (How), no results are reported for the t-test and Bayes factor because the standard deviation in Group B was 0.

Therefore, regarding RQ1, no statistically significant effects of the visualizations in SedVis on the participants’ action planning were found. The Bayes factors indicated weak evidence towards no difference between the two groups except for the perceived viability.

Regarding the specificity (“When”) of action plans, some unexpected patterns were observed, especially in Group B. Two participants (B3 and B6) in Group B always entered the current time when they made the plan. They explained in the exit interview that each of their plans was actually what they were about to do at the moment when they logged the plan. Participant B6 further commented that they found it difficult to make action plans for the future because they were not sure
about her behavior patterns. Besides, another three participants always used vague cues to specify the “When”: Participant B1 used “today”; Participant B4 used “anytime”; Participant A5 used “today.” **Table 3** shows a summary of the “When,” “Where,” and “How” in the participants’ action plans.

**Table 3. Summary of “When,” “Where,” and “How” components identified in the participants’ action plans.**

| When      | Where                        | How                                                  |
|-----------|------------------------------|------------------------------------------------------|
| Timepoint (e.g., 4 am) | Workplace (e.g., university, lab, library, campus, garden, office, building Z, outdoor) | Walk (e.g., tea walk, walk to post, walk between lectures, walk after lecture/meeting/lunch/dinner, 5-min walk, 6000 steps, 250 steps per hour) |
| Now       |                              |                                                      |
| Vague time (e.g., today, tomorrow, anytime) | Home/Dormitory/Kitchen |                                                      |
|           | City                         |                                                      |
|           | Park                         |                                                      |

**RQ2: Changes in Participants’ Sedentary Behavior**

A mixed ANOVA showed no statistically significant effect of time ($F_{1,14}=0.14, P = .72$), group ($F_{1,14}=0.17, P = .68$), or the interaction between time and group ($F_{1,14}=0.84, P = .38$) on sedentary hours. The result of the Bayesian paired samples t-test suggested (with weak evidence) that the daily sedentary hours decreased from the baseline week to the intervention weeks in group A ($BF_{+0} = 1.922, M = 0.522, CI [0.044, 1.251]$). This is also mirrored in the descriptive statistics plotted in **Figure 9** (mean -0.40, SD 0.63). By contrast, in group B, it was more likely that the intervention had no effect than a positive effect with moderate evidence ($BF_{+0} = 0.278, M = 0.175, CI [0.007, 0.644]$; mean 0.17, SD 1.65).
Therefore, regarding RQ2, the intervention involving the visualizations and action planning in SedVis had a positive effect on reducing participants’ sedentary hours with weak evidence. Meanwhile, action planning alone had no effect on reducing participants’ sedentary hours with moderate evidence.

After answering RQ1 and RQ2, we further applied (Bayesian) Pearson correlation analysis to explore the correlation of participants’ behavior change of sedentary hours with the number of total action plans ($r = 0.051, P = .850, BF_{01}=3.189$), the number of unique action plans ($r = -0.150, P = .580, BF_{01}=2.813$), the perceived viability of action plans ($r = 0.018, P = .947, BF_{01}=3.235$), the perceived instrumentality of action plans ($r = -0.029, P = .914, BF_{01}=3.224$), and the perceived specificity (the mean specificity of “When”, “Where” and “How” as shown in Table 2) of action plans ($r = 0.367, P = .163, BF_{01}=1.318$). No statistically significant correlation was found, while the Bayes factors suggested weak to moderate evidence towards no correlation between participants’ behavior change of sedentary hours with the factors of their action plans.

**RQ3: Participants’ Interaction with SedVis**

The frequency of checking the visualizations per day reflects the participants’ strength of self-monitoring, which might also act as a cue for self-reminding of sedentary behavior change. **Figure 10** shows the daily frequency of participants checking the visualizations in SedVis. Participants were more likely to check the visualizations from the notification bar (68.33%) than from the dashboard (31.67%).
To test the assumption that the participants' engagement with the app is positively associated with the effect of the app on their behavior, the daily frequency of participants checking the visualization in SedVis was correlated with their change of sedentary hours, calculated as daily sedentary hours during the intervention weeks minus the counterparts during the baseline week (see Figure 11). A Pearson correlation did not show a statistically significant correlation between participants' checking the visualizations in SedVis with the change of daily sedentary hours \((r = -0.498, P = .21)\), although the effect was large [53]. Then a Bayesian Pearson correlation with the alternative hypothesis of negative correlation was calculated. The Bayesian factor \((BF_{-0} = 1.489, r = -.496)\) weakly suggested that the two factors were more likely to be negatively related than unrelated. To some extent, this confirmed that the participants' engagement was positively related to the effect of reducing sedentary hours.

\[ \text{Figure 10. The daily frequency of participants checking the visualizations in SedVis through the notification and the home screen.} \]

\[ \text{Figure 11. The scatter plot of the participants' daily frequency of checking the visualizations and their change in daily sedentary hours in group A. The change of daily sedentary hours (x-axis) equals to the daily sedentary hours} \]
during the intervention weeks minus the counterparts during the baseline week. Thus, negative values indicate a reduction in sedentary behavior.

RQ4: User Experience

User experience was investigated both quantitatively and qualitatively. By comparing the ratings to the benchmark provided by the UEQ toolkit [8], the participants’ scores of user experience were mapped to quality levels, as shown in Table 4.

Table 4. The user experience scores based on UEQ.

| UEQ Scales    | Mean (Group A) | Comparison to Benchmark | Mean (Group B) | Comparison to Benchmark | t₁₄  | P    | Cohen’s d |
|---------------|----------------|-------------------------|----------------|-------------------------|------|------|-----------|
| Attractiveness| 1.65           | Good                    | 1.44           | Above average           | 0.60 | .56  | 0.3       |
| Perspicuity   | 2.25           | Excellent               | 2.10           | Excellent               | 0.47 | .64  | 0.24      |
| Efficiency    | 1.91           | Excellent               | 1.84           | Excellent               | 0.19 | .85  | 0.10      |
| Dependability | 1.34           | Above Average           | 1.22           | Above Average           | 0.32 | .75  | 0.16      |
| Stimulation   | 1.66           | Good                    | 1.16           | Above Average           | 1.72 | .11  | 0.86      |
| Novelty       | 1.22           | Good                    | 0.44           | Below Average           | 2.75 | .02  | 1.37      |

According to the results of Bayesian t-test with the alternative hypothesis that Group A scored higher than Group B, visualizations yielded more perceived stimulation (BF₁₀ = 1.989, M = 0.621, CI [0.045 1.622]) and novelty (BF₁₀ = 7.439, M = 1.025, CI [0.160, 2.163]). For other aspects, the scores tended to be equivalent. It was observed that the previewed dependability is only “above average,” which means the participants did not think the data shown in the app were very accurate. According to the exit interview, several participants believed their steps were underestimated based on two reasons: (1) the sensors in some smartphones were not very sensitive; (2) they did not take the smartphone with them during some indoor activities, e.g., going to the restroom or walking in the laboratory.

Even though participants were asked to make at least one action plan every day during the two-week intervention phase, the average number of daily action plans was only 0.59, which hints that participants might not have used the app regularly. Regarding user acceptance, no participant complained about interruptions of daily activities through using the app, while some participants commented that making action plans every day was boring. Eight participants wanted to keep the app and continue using it for reducing sedentary behavior, while four participants implied they needed a reminder if they continued to use the app. Four participants said they did not want to continue to use the app for the following reasons: (1) “it underestimates my steps”; (2) “I do not want to always keep the GPS on”; (3) “the app provided too little new information”; (4) “I need a reminder for enacting my plans.”
Discussion

Principal Findings

This paper presents a pilot test of SedVis, an app-based sedentary behavior intervention that aims to reduce sedentary behavior through a combination of mobility pattern visualization and daily action planning. Specifically, it was hypothesized that mobility pattern visualization would lead to improved action plans, which would, in turn, lead to a reduction in sedentary hours.

Contrary to this expectation, the visualizations did not impact on the participants’ action planning (see the results in terms of RQ1). However, these results are in line with Maher and Conroy [5], who also found no effect of daily action planning on reducing sedentary behavior in the short term among college students. Furthermore, data suggested that sedentary behavior change did not correlate with the quantity and quality action plans. As explained by Maher and Conroy [5], one reason for the ineffectiveness could be that the cue-to-action response expected by action planning relies much on the conscious self-regulatory process, which is difficult for highly habitual behavior, such as sedentary behavior. Another explanation could be based on prospective memory [54] inspired by the work of Grundgeiger and colleagues [55]: Prospective memory tasks, which require us to remember to do something at a future time, are very difficult especially when focusing on other tasks. Because sedentary behavior is often coupled with other tasks demanding attention, the action plans of reducing sedentary behavior might be easily forgotten.

Still, SedVis may be effective in reducing sedentary behavior: When having had access to mobility pattern visualizations, the intervention group slightly reduced sedentary hours compared to baseline. At the same time, the control group did not show a reduction in sedentary hours. It could thus be concluded that visualizations might have impacted sedentary behavior by promoting awareness when self-monitoring sedentary behavior [56]. This idea is supported by the association between the change of sedentary time and the participants’ engagement with SedVis. Engagement with the app, in turn, might have been strengthened by the stimulation and novelty of the visualizations. As Perski et al. [57] pointed out in their review on engagement with behavior change interventions, novelty is positively related to engagement as it prevents boredom. The inclusion of novel and stimulating visualizations may thus indirectly influence behavior change.

The participants’ evaluations of SedVis with visualizations were good or excellent regarding the attractiveness, perspicuity, efficiency, stimulation, and novelty. Only the perceived dependability was above average. This may reflect some participants’ concerns that SedVis underestimated their steps. At the exit interview, several participants mentioned that they believed the app missed part of their daily steps because they did not take the smartphone with them for certain activities (e.g., working in the laboratory). This limitation of the present study could be avoided in future studies by using wearable sensors (e.g., wristbands, posture monitors, see [58]).
The results of the present study support the notion that smartphone apps might be an effective tool to reduce sedentary behavior in daily life (see [13,59] for reviews). However, they also indicate that behavior change techniques might differ in their effectivity to induce changes in sedentary behavior. Three commonly used behavior change techniques were used in the present study, i.e., self-monitoring, feedback, and action planning [31,59]. Interestingly, action planning was not sufficient to induce changes in sedentary hours in the active control group, while additional feedback visualizations induced a small reduction in sedentary hours in the intervention group. Thus, it could be concluded that engaging visualizations to provide feedback on behavior might be more effective in inducing a change in sedentary behavior than action planning. However, as the sample of the present study was small, further studies are needed to identify which behavior change techniques are most effective for sedentary behavior change.

Implications for Future Work

Rethinking Action Plans

While most participants made action plans in accordance with the format of specifying “When,” “Where,” and “How” to reduce their sedentary time, one participant additionally enclosed other contextual cues in their plans. For example, “15:00, lab, take a walk in between experiments” and “13:00, uni, walk between lectures.” Because of the additional cues - experiment and lectures here - the plans might be easier to remember. These plans are in line with the “if-then” format of implementation intentions, which emphasize the contextual cues linking to the goal-directed behavioral response [24,60]. As sedentary behavior is prevalent, the cues of “When” and “Where” might provide limited strength of conditional links to the response behavior. Due to the requirement of less self-regulatory resources, the more contextual plans in the “if-then” format might be more effective than the plans in “when, where, and how” format [5,60]. However, no prior studies have assessed potential differential effects in sedentary behavior change.

Relating to SedVis, future work might explore how the app could support personalized implementation intentions and their effectiveness on sedentary behavior change, such as generating recommendations of plans based on users’ mobility patterns and context, which they might not even notice. Several heuristic rules could be used, e.g., going to the restroom downstairs instead of the nearest one, or more frequently going to the kitchen to drink water. Armitage [61] found that experimenter-provided and self-generated implementation intentions could be equally effective in reducing alcohol consumption. It is worth investigating this effect on sedentary behavior change following the study design. Some participants commented that making plans every day was boring, so generating plan-recommendations might also increase user acceptance in the long term.

Rethinking Self-Monitoring, Feedback, and Reminders

Since the present study suggests that higher interaction frequency could lead to a greater reduction of sedentary behavior, future work might need to study more convenient and intuitive user interfaces (e.g., glanceable feedback [62]) to simplify
self-monitoring and interaction with the app even further. In the current version of SedVis, the easiest way to access the daily visualization was to swipe down the notification bar and click on the notification. In a future version, the app could display the real-time sedentary information using an always-on progress bar [63] embedded in the notification or the app widget on the smartphone’s home screen.

Future work should also consider the users’ need for reminders. Participants expressed differential attitudes towards reminders: Some of them expressed that reminders for the action plans they made would be helpful because they sometimes forgot the plans; others thought that reminders would be unnecessary because of the potential interruption. Although fixed-time reminders (e.g., prompts on PC screens) were frequently used in prior interventions for reducing sedentary behavior at work [64], no studies explored the effectiveness and user experience of the reminders for personalized action plans.

Limitations
The present study contained several limitations. First, the present study determined sedentary hours based on activity tracked with the smartphone, which may be less valid than using dedicated activity trackers (e.g., activPAL and ActiGraph) [37]. However, having to wear additional devices might be inconvenient for users (e.g., charging the device and attaching the device to the thigh) and thus also bias results. Moreover, the sedentary hours based on the app-logged data might underestimate the participants’ movements. One reason for this might be that participants might not take the smartphone with them during certain activities such as going to the washroom. Another reason could be that some activities could not be recognized and counted as steps. For example, one participant made an action plan to do push-ups at home, which cannot be recognized and recorded using a smartphone’s sensors.

Second, the app did not differentiate sleeping time from the sedentary time, and it was assumed the participants’ sleeping time was consistent during the study. Although participants were asked if their sleeping time was normal in the exit interview, their recall might not be accurate.

Third, the sample size is small. The small sample size and the relatively large between-subjects variances of the measurements might be the reason for several weak conclusions. For example, the means of the number of action plans, the number of unique action plans, and specificity (“When” and “Where”) were higher in Group A than in Group B, but only statistically weak evidence could be found.

Lastly, the study period is relatively short, which limits the validation of the results in short-term scenarios. Therefore, future studies should replicate the present results in larger samples and with longer study duration.

Conclusions
This paper presents the results of a pilot study in which the effect of a novel visualization within a mobile application on users’ action planning and sedentary
behavior change was evaluated. The results suggest that using a smartphone app to collect mobility data and provide feedback in real-time using visualizations might be a promising method to induce changes in sedentary behavior and might be more effective than action planning alone. Future research should thus further explore the potential of the visualizations of users’ sedentary behavior to induce behavior change.

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