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Sensor-triggered ecological momentary assessment in physical activity and sedentary behaviour research among Belgian community-dwelling elderly: lessons learnt from intensive longitudinal studies

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ABSTRACT

Objectives Regular physical activity (PA) and reduced sedentary behaviour (SB) have been associated with positive health outcomes, but many older adults do not comply with the current recommendations. Sensor-triggered ecological momentary assessment (EMA) studies allow capturing real-time data during or immediately after PA or SB, which can yield important insights into these behaviours. Despite the promising potential of sensor-triggered EMA, this methodology is still in its infancy. Addressing methodological challenges in sensor-triggered EMA studies is essential for improving protocol adherence and enhancing validity. Therefore, this study aimed to examine (1) the patterns in sensor-triggered EMA protocol adherence (eg, compliance rates), (2) the impact of specific settings (eg, event duration) on the number of prompted surveys, and (3) participants' experiences with engaging in a sensor-triggered EMA study.

Design Two longitudinal, sensor-triggered EMA studies—one focused on PA and the other on SB—were conducted using similar methodologies from February to October 2022. Participants' steps were monitored for seven days using a Fitbit activity tracker, which automatically prompted an EMA survey through the HealthReact smartphone application when specified (in)activity thresholds were reached. After the monitoring period, qualitative interviews were conducted. Data from both studies were merged.

Setting The studies were conducted among community-dwelling Belgian older adults.

Participants The participants had a median age of 72 years, with 54.17% being females. The PA study included 88 participants (four dropped out), while the SB study included 76 participants (seven dropped out).

Primary and secondary outcome measures Descriptive methods and generalised logistic mixed models were employed to analyse EMA adherence patterns. Simulations were conducted to assess the impact of particular settings on the number of prompted EMA surveys. Additionally, qualitative interview data were transcribed verbatim and thematically analysed using NVivo.

Results Participants responded to 81.22% and 79.10% of the EMA surveys in the PA and SB study, respectively. The confirmation rate, defined as the percentage of EMA surveys in which participants confirmed the detected behaviour, was 94.16% for PA and 72.40% for SB. Logistic mixed models revealed that with each additional day in the study, the odds of responding to the EMA survey increased significantly by 1.59 times (OR=1.59, 95% CI: 1.36 to 1.86, p<0.01) in the SB study. This effect was not observed in the PA study. Furthermore, time in the study did not significantly impact the odds of participants confirming to be sedentary (OR=0.97, 95% CI: 0.92 to 1.02, p=0.28). However, it significantly influenced the odds of confirming PA (OR: 0.81, 95% CI: 0.68 to 0.97, p=0.02), with the likelihood of confirming decreasing by 19% with each additional day in the study. Furthermore, a one-minute increase in latency (ie, time between last syncing and starting the EMA survey) in the PA study decreased the odds of the participant confirming to be physically active by 20% (OR: 0.80, 95% CI: 0.72 to 0.89, p<0.01). Simulations of the specific EMA settings revealed that reducing the event duration and shorter minimum time intervals between prompts increased the number of EMA surveys. Overall, most participants found smartphone usage to be feasible and rated the HealthReact app as user-friendly. However, some reported issues, such as not hearing the notification, receiving prompts at an inappropriate time and encountering technical issues. While the majority reported that

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study focused on sensor-triggered ecological momentary assessment (EMA) to examine short bouts of physical activity and sedentary behaviour, minimising recall bias.
⇒ Data from two innovative sensor-triggered EMA studies were combined to examine EMA adherence, optimal EMA settings and participant experiences.
⇒ A combination of quantitative and qualitative methods was used in this study, enhancing the depth and comprehensiveness of the findings.
⇒ Adults aged 65 years and older were recruited, limiting the generalisability of the lessons learnt to other populations.

their behaviour remained unchanged due to study participation, some noted an increased awareness of their habits and felt more motivated to engage in PA. **Conclusions** This study demonstrates the potential of sensor-triggered EMA to capture real-time data on PA and SB among older adults, showing strong adherence potential with compliance rates of approximately 80%. The SB study had lower confirmation rates than the PA study, due to technical issues and discrepancies between self-perception and device-based measurements. Practical recommendations were provided for future studies, including improvements in survey timing, technical reliability and strategies to reduce latency.

INTRODUCTION

Performing regular physical activity (PA) and interrupting and limiting sedentary behaviour (SB) have been associated with significant physical and mental health benefits.[1–3] However, despite the general consensus about the beneficial effects of PA, 3%–7% of UK older adults aged over 65 do not meet the global recommended levels of at least 150 min of moderate-intensity or 75 min vigorous-intensity PA per week, as measured by device-based methods.[4 5] In addition, although recent guidelines urge people to limit and interrupt SB, older adults aged 65 years and older spend on average more than 10 hours in sedentary activities per day[6] and nearly half of their sedentary time in sedentary bouts that last longer than 30 min.[7] Growing evidence indicates that sedentary time is a major risk factor for numerous adverse health outcomes, including type 2 diabetes, metabolic syndrome, cardiovascular disease, cancer and increased mortality risk in both adult and older adult populations.[8–11] Furthermore, prolonged sedentary bouts (≥30 min) have been associated with negative physiological consequences, including reduced glucose metabolism, impaired lipid profiles and increased inflammation markers, all of which contribute to heightened cardiometabolic risk.[12] Therefore, promoting PA and interrupting and limiting SB remain important health priorities.

A novel and promising approach for promoting PA and interrupting and limiting SB is the use of Just-in-Time Adaptive Interventions (JITAIs). JITAIs provide behavioural support at the right time and in the most conducive environmental and social context (ie, when the person needs it most and is most likely to be receptive). For example, encouraging prompts can be delivered when an individual is at risk of engaging in prolonged SB or when he/she is in a favourable context to initiate a PA session.[13] To enhance the development of effective JITAIs, it is imperative to acquire a deeper understanding of the time-dependent and context-dependent factors influencing PA and SB within and between individuals.

One valuable approach for gaining such insights is through the application of ecological momentary assessment (EMA) studies. EMA is a data collection method, enabling repeated sampling of behaviours and experiences in participants' natural environment.[14] By capturing real-time data, EMA maximises ecological validity and minimises recall bias, offering benefits compared with retrospective questionnaires.[15] Using brief assessments, EMA can shed light on the factors influencing individuals' engagement in PA or SB in specific contexts, providing opportunities to explore context-dependent and time-dependent determinants of behaviour.[16]

Time-based and event-based sampling are the most commonly used methods in EMA research. Time-based sampling assesses participants' current behaviour and experiences during specified or random moments of the day, aiming to identify determinants more broadly without a predefined focus on events.[15] This method may involve administering surveys at fixed intervals (eg, every two hours), fixed timepoints (eg, every morning at 10:00) or at random moments during the day to assess determinants and behaviours in participants' natural environments. This approach enables researchers to investigate the fluctuations of these determinants and behaviours within an individual over time. However, when investigating a specific behaviour like PA, the likelihood of a prompt occurring during a PA event (such as a 10 min jogging event) is relatively low. Therefore, event-based sampling (also called event-contingent or context-sensitive EMA) offers the possibility to examine real-time contexts in which individuals are physically active and/or sedentary.[15] Historically, event-based sampling relied on self-initiation of the surveys. However, recent technological advances in wearable sensors enable researchers to prompt a survey automatically when the behaviour of interest occurs, providing them with the opportunity to fine-tune event-based sampling methods in PA and SB research.[17] This sensor-triggered approach, where the device itself prompts surveys based on real-time behaviour, shows promising potential, though sensor-triggered event-based EMA studies remain underrepresented in literature.[18–21]

A potential reason for this under-representation might be that sensor-triggered EMA is accompanied by various methodological and technological challenges. Clear methodological and technological guidelines for the development of a sensor-triggered EMA study on PA and SB are currently lacking but could positively impact EMA protocol adherence and ecological validity of the results. In the context of sensor-triggered EMA studies, setting optimal prompting rules (ie, predefined thresholds that need to be exceeded to initiate a sensor-triggered survey) is of utmost importance. Event duration, step count, the use of outliers (ie, minutes with activity that exceed or fall below the predefined threshold for triggering EMA surveys), and other settings can affect the number of surveys that will be prompted. Moreover, there are currently only suggestions rather than established guidelines on the optimal prompt frequency to ensure adequate data collection while minimising participant burden. To avoid sending multiple surveys within a short time frame or during a single event, it is important to set an appropriate time interval between two prompts. However, optimal time intervals between two EMA prompts have yet to be established. To address these gaps and enhance the design of future EMA studies, it is

Table 1 Keywords and their definitions

Keywords	Definition
Device-initiated ecological momentary assessment	A method where devices automatically prompt real-time surveys based on detected behaviours, capturing immediate data and reducing recall bias
Compliance rate	The ratio of completed surveys to the number of prompted surveys
Confirmation rate	The rate of events that were confirmed by the participants
True positive rate	The proportion of correctly prompted events that were responded to

crucial to explore how these specific settings affect the number of surveys. However, there is no universal solution, as optimal guidelines may vary between PA and SB and depend on specific research questions. Additionally, sensor-triggered EMA is accompanied by several technical challenges. For instance, incorrectly triggered EMA surveys can increase participant burden and lead to frustration, reduced engagement or incomplete data collection. This can be assessed by calculating the 'true positive rate', which is the proportion of true PA or sedentary events that resulted in prompts (detected by an accelerometer) and were responded to, relative to the total (ie, true and false) prompted EMA surveys. A summary of the definitions can be found in table 1.

Optimising these methodological and technical issues could lead to greater compliance with EMA protocols, which is crucial to obtain ecologically valid data. Currently, there is extensive research on the impact of event duration and prompt frequency on adherence in EMA studies.[22–24] However, research on the practical aspects of implementing sensor-triggered EMA remains limited. For example, compliance can be influenced by factors like prompt latency (the delay between an event and when the prompt is delivered). If too much time passes between the detected behaviour and the EMA prompt, participants may perceive the survey as irrelevant or disconnected from their behaviour. Typically, compliance is expressed as the ratio of completed surveys to the number of prompted surveys.[25] It can be anticipated that compliance decreases throughout the study period because of participant fatigue. Furthermore, understanding participants' experiences with sensor-triggered EMA studies, particularly among older adults, is critical, as there are still more challenges associated with using digital solutions in this age group compared with others.[26] This can offer valuable insights into the acceptability, feasibility and challenges of the study protocol, as well as provide suggestions for improving future EMA studies focusing on PA and SB in older adults.

The main objective of this study is to summarise lessons learnt from conducting two sensor-triggered EMA studies, one on PA and the other on SB, among older adults, and provide practical recommendations for future sensor-triggered EMA studies in these areas. Specifically, we aim to (1) explore patterns in protocol adherence throughout the study, assessing both compliance and confirmation rates (ie, the rate at which participants confirmed the events) and investigating how these rates vary by study day and prompt latency; (2) examine technical and methodological aspects, including the true positive rate (ie, the proportion of accurately prompted events that were responded to) and the influence of specific EMA settings (eg, event duration) on prompt frequency and (3) gain insights into older adults' experiences regarding their participation in a sensor-triggered EMA study.

METHODS

Participants

Two observational, sensor-triggered EMA studies were performed from February to October 2022 in Flanders, Belgium. One study focused on PA (n=88), the other study focused on SB (n=76). Participants in both studies were recruited through purposeful convenience sampling by reaching potential participants via organisations for older adults, social media and word-of-mouth in the social network of the involved researchers. Participants were excluded from the study if they had been diagnosed with cognitive impairments (eg, mild cognitive impairment, dementia) or were not able to walk at least 100 m independently.

Procedure

During the first home visit, an intake survey was conducted to assess participant characteristics, including age, sex, height, weight and familiarity with smartphones. Participants were then equipped with a Fitbit activity tracker (Inspire 2 or Ionic models) and a smartphone with data-SIM (Motorola E40 or G20), on which the sensor-triggered EMA app and Fitbit app were installed. The sensor-triggered EMA studies lasted for seven consecutive full days, starting on the day after the first home visit. Every evening before going to bed, participants were asked to register information regarding any prompts they might have missed during the day or technical issues they encountered. A second home visit was planned to gather the materials and to conduct a semistructured interview on participants' user experience and the feasibility of the study. The study was reported according to the Strengthening the Reporting of Observational Studies in Epidemiology checklist (see online supplemental file 1).

Materials and measures

Fitbit activity tracker

The Fitbit activity tracker serves as a suitable monitoring device in EMA studies due to its user-friendliness and capability to capture short bouts of PA and/or SB in real-world settings.[27–29] Participants wore either the Fitbit Ionic or Fitbit Inspire 2 on their non-dominant wrist throughout the study periods to track their minute-by-minute step

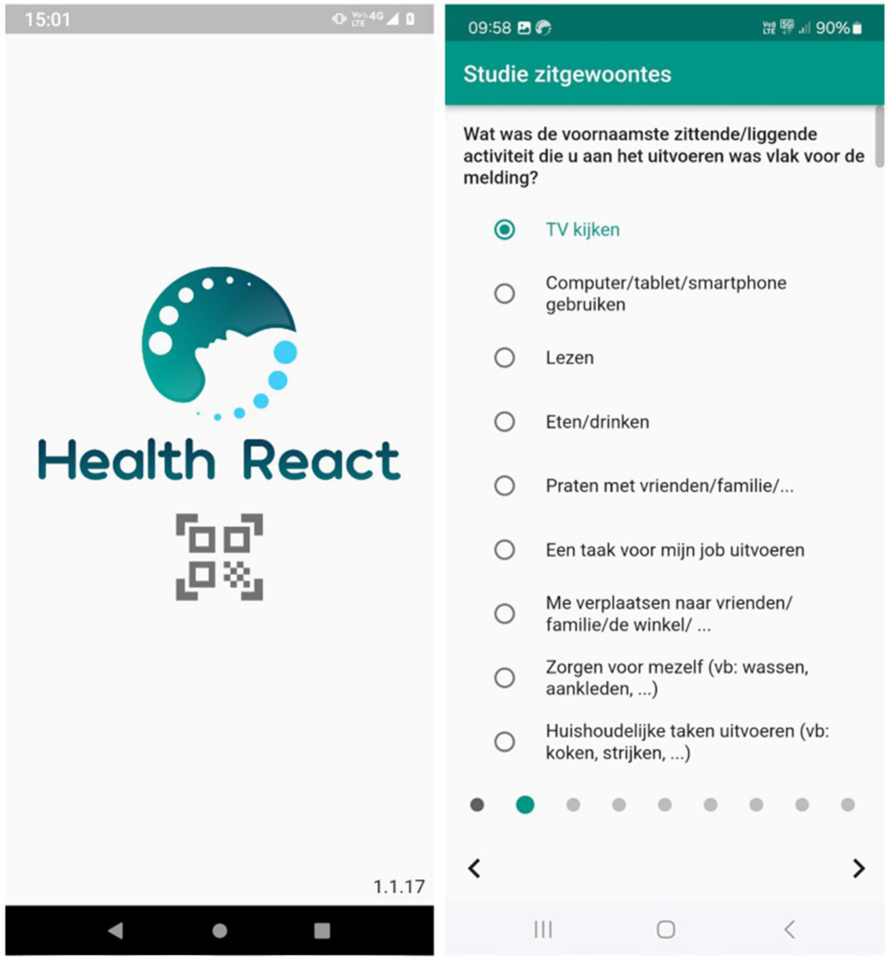

Figure 1 Screenshots from the HealthReact application on a smartphone.

count and heart rate. To ensure continuous real-time monitoring of daytime behaviour, participants charged the Fitbit only at night. The Fitbit application syncs with the Fitbit server approximately every 15 min via internet connection. However, this may have caused a latency between the measured behaviour and the prompt. During the first home visit, we reviewed all survey items with participants, specifically explaining that, due to the synchronisation interval, it was possible for a prompt to arrive a little later than the actual behaviour. This clarification ensured participants understood the timing aspect.

HealthReact

Both studies used HealthReact (V.1.62, University of Hradec Kralove, Czechia) as a web-based platform, accompanied by a smartphone-based application to trigger EMA prompts (figure 1). The platform supports time-based, as well as sensor-triggered EMA sampling. Since HealthReact is connected with Fitbit servers in real-time, making the data accessible via the Fitbit Application Programming Interface (API) via internet connection, a survey can be elicited during or immediately after a specific event or behaviour of interest. To automatically elicit an EMA survey based on real-time PA or SB, predefined prompting rules are required. A prompting rule can be created based on metrics such as average or accumulated steps, minutes categorised by activity intensity (eg, fairly active, lightly active, very active or sedentary), heart rate, etc over a certain time period. In addition, HealthReact also provides the possibility to create an end rule (ie, an end rule initiates a standby mode during which the sensor-triggered EMA application becomes receptive and waits for the end rule to be fulfilled).

The following HealthReact settings were applied for both substudies. The maximum number of prompts was limited to six per day to avoid overburdening the participants.[16 19] The EMA surveys were required to be completed within 30 min. Reminders were scheduled to be sent at 10 and 20 min following the initial prompt and then, during the final five minutes of the 30-minute time span, reminders were sent every minute. The EMA surveys always consisted of 12 (PA study) and 14 (SB study) questions. The first one was a confirmation question (ie, "Were you actually being physically active just before the survey was prompted?" for the PA study, and "Were you actually sitting at this moment or just before the survey was prompted?" for the SB study). Subsequent questions covered the type of activity, the participants' physical and social context, and various affective and physical states.

Table 2 Overview of the procedures of both sensor-triggered EMA studies

	PA study	SB study
Number of participants (n)	88	76
Start rule		
Steps	5’ ≥60 steps per minute	30’, 0 steps per minute
Heart rate	/	>40 bpm
End rule	2’ ≤10 steps per minute	/
Minimum sampling interval	60’	120’
Sampling frequency	max. 6/day	max. 6/day
Study duration	7 days	7 days
Survey expiry time	30’	30’
Max. number of items per prompt	12	14
Interview participants (n)	25	41

bpm, beats per minute; EMA, ecological momentary assessment; PA, physical activity; SB, sedentary behaviour.

If the participant indicated not to be active/sedentary before the survey was prompted, the survey was stopped. Finally, considering Fitbit’s syncing interval of approximately 15 min, the maximum time interval to detect an event in the past was set at 20 min, allowing an extra five minutes for unexpected delays in data transmission and processing to ensure all walking and sedentary events were captured.

PA settings

To capture sustained walking bouts of at least five minutes, the start rule was set at ≥60 steps per minute. This threshold was expected to capture walking bouts with a sensitivity and specificity of approximately 99% and 98%, respectively.[29] However, since the total number of events per participant was low for the first 12 participants, the protocol was adapted to allow one outlier (ie, one minute with less than 60 steps) during the five-minute walk for the remaining participants. In addition, to prevent interrupting the walking bout with an EMA prompt, an end rule was implemented. Only when the start rule (ie, at least five minutes, 60 steps/minute) was followed by two consecutive minutes of 10 or fewer steps per minute was the EMA survey prompted. Finally, a minimum interval of 60 min was set between two prompts to ensure an even distribution of prompts throughout the day and to capture a diverse range of PA. For an overview, see table 2.

SB settings

A survey was prompted after 30 consecutive minutes of zero steps. To avoid prompting surveys about SB during non-wear, an additional start rule based on heart rate greater than 40 beats per minute was implemented. No end rules were set for SB settings. To ensure a good distribution of prompts during the day, an interval of at least 120 min between prompts was set. In addition, to prevent prompting surveys during the night, a time interval from midnight to 6:00 hours was set during which no prompts could be sent. All survey prompts in the SB study were cross-checked against the Fitbit step data, and only the valid prompts (ie, those triggered during wear time) were retained for data analysis. For an overview of these settings, see table 2.

Interviews

After participation in the EMA study, semistructured interviews were conducted with the first 25 (PA study) and 41 (SB study) participants, until data saturation was reached. This allows for both predefined questions and open-ended explorations. Participants were asked about their overall experience with the EMA study, including the user-friendliness of the devices (Fitbit activity tracker and smartphone) and HealthReact, as well as the perceived accuracy, timing and number of surveys. See online supplemental files 2 and 3 for the interview guides for the PA and SB study, respectively. The interviews were audio-recorded and conducted at the participants’ home to ensure participant comfort and confidentiality. The study was conducted and reported in accordance with the Standards for Reporting Qualitative Research (SRQR) checklist (see online supplemental file 4).

Patient and public involvement

Patients and the public were not directly involved in the research process, as this study combined results from two separate studies. However, each study individually tailored EMA items to the target group. Before developing the EMA surveys, the most commonly held beliefs about PA and SB (modal salient beliefs) among non-active older adults were identified through qualitative interviews.[30 31] Additionally, an activity diary was used to explore potential activities for inclusion in the EMA survey, ensuring the survey items were well-aligned with the experiences and needs of the target group.

Data processing and statistical analyses

Analyses were performed using RStudio (R V.4.3.1). To address the first aim, descriptive statistics were computed to evaluate the protocol adherence, including the number of surveys sent to participants, the number of ignored surveys, and the number and rate of answered surveys per participant (ie, compliance rate). Furthermore, the number and rate of responded surveys in which the behaviour was confirmed (ie, confirmation rate) were calculated based on all correctly triggered events. Graphs were generated to illustrate compliance rates and likelihood of confirming the behaviour in prompts over the study period. Subsequently, generalised logistic mixed models (random intercept–fixed slopes) were conducted to investigate how the likelihood to respond and the likelihood to confirm the behaviour of interest fluctuate over time using the lme4 package.[32] These models reflected the hierarchical structure of the data, which consisted of three levels: repeated measurements nested within days, which are in turn nested within individuals. A null model was run to estimate the between and within subject variance using the intraclass correlation coefficient (ICC). The outcome variables (compliance and confirmation) were defined as binary (ie, whether a response was given or not, and whether an event was confirmed by the participants or not). Four separate models were estimated, one for each outcome variable within each study. Time in the study served as the independent continuous variable, calculated as the number of days between the study start date and the date of each EMA survey response. To avoid overfitting, the random effect for days was removed when necessary (ie, all models with 'time in the study' as an independent variable), based on model diagnostics such as singular fit warnings or near-zero variance components. Since time in the study was equally distributed over participants, it can be assumed that our current models primarily captured variability at the within-subject level. To assess model assumptions, we examined Cook's distance to detect potential influential observations that might disproportionately affect the estimated fixed or random effects and checked for linearity in the relationship between continuous predictors and the logit of the predicted outcomes. When the linearity assumption was violated, the independent continuous variable was log transformed. Subsequently, we investigated the effect of prompt latency (ie, time between last syncing and starting the EMA survey) on prompt confirmation. However, the version of HealthReact we used in this study did not record the exact timestamps for when the survey was prompted, only logging the time when participants began their responses. For the PA study, we determined the prompt timing by identifying the timestamp of the sync that occurred after the stepping event but prior to the response start. However, this method could not be applied to the SB study since participants often had multiple syncs during the sedentary event, making it impossible to unequivocally pinpoint the prompt timing. Therefore, prompt timing and latency were not computed in the SB study. To investigate whether prompt latency predicts the likelihood of validating the prompt in the PA study, an additional generalised logistic mixed model was run. An interaction effect between prompt latency and time in the study was incorporated into the model, since it was hypothesised that the relationship between confirmation and prompt latency might be moderated by the day in the study.

For the second aim, we calculated the proportion of surveys that were truly triggered by walking or sedentary events (as recorded by Fitbit) divided by the total triggered surveys that were answered (ie, true positive rate), and the incidence of technical issues encountered by participants. Descriptive statistics for both study samples, such as age, gender, BMI and average daily steps, were also computed. In addition, to calculate the expected number of prompts for various sensor-triggered EMA settings, a series of simulations were conducted using data recorded by Fitbit. Minute-by-minute step count data were used to simulate walking events, while both heart rate and step count data were used to simulate sedentary events. First, the original settings used in both studies were replicated to calculate the total number of inactivity and walking bouts under ideal settings (ie, assuming no technical issues and a continuous internet connection). For walking events, these were five minutes of ≥60 steps, one outlier, time span set to 20 min backwards and a minimum time interval of 60 min in between two prompts; for sedentary events: 30 min of zero steps, maximum time interval to detect an event in the past set to 20 min (ie, time backwards) and a minimum time interval of 120 min in between two prompts, while measuring a heart rate of >40 beats per minute. For the simulation of walking events, the two-minute inactivity end rule was not applied due to its computational complexity. However, our focus was solely on examining how specific settings impact the number of EMA surveys and not to compare simulated with actual prompts. In a second step, we modified these specific settings (ie, step count, event duration, time backwards, minimum time interval in between two prompts and number of outliers) and re-ran the simulations to understand how specific changes in EMA settings impact the number of daily prompts per participant. For all simulations of sedentary events, the step count threshold for prompting a survey was adjusted to ≤2 steps per minute, instead of zero, based on the recent validation study.[29]

Qualitative data from semistructured interviews

Finally, the audiotapes of the interviews were transcribed verbatim and processed with NVivo V.12.1 to address the third aim. The data were analysed using a deductive approach; various aspects regarding the EMA study were thematically analysed, using three key themes: HealthReact, prompts and participant experiences. The HealthReact theme included subthemes of feasibility and user-friendliness of the HealthReact application. The prompts theme encompassed the perceived accuracy of prompts, their effects on behaviour, encountered problems, timing and the amount of prompts. Lastly, the theme about participant experiences was divided into subthemes of smartphone usage, study duration and general experiences. The two largest themes (ie, prompts and participant burden) were visually presented in two Pen Profiles to enhance clarity.

RESULTS

Participant and study characteristics

Initially, 92 individuals were recruited for the PA study, and 83 for the SB study. However, four participants from the PA study and seven participants from the SB study did not complete the 1-week assessment period, due to stress related to study participation (PA study: n=4; SB study: n=5) or illness (SB study: n=2). Therefore, the final study sample consisted of 88 and 76 participants for the PA and the SB study, respectively. Table 3 provides the descriptive

Table 3 Participant characteristics and protocol adherence

Characteristics	Study PA (n=88)	Study SB (n=76)
Age (years; median±IQR)	71.00±10.00	73.00±10.00
Sex		
Female (%)	49.44	58.90
BMI (kg/m²; mean±SD)	26.49±4.01	25.62±3.62
Marital status		
Married or cohabiting (%)	70.79	64.38
Education		
Higher (%)	32.58	43.06
Daily steps (median±IQR)	8126±7752	7041±5567
Familiar with smartphone (%)	78.8%	76.32%
Total number of prompts sent	884	2579
Prompts per participant (median±IQR)	9±9	36±11
Compliance rate (n)	81.22% (718)	79.10% (2074)
Confirmation rate (n)*	94.16% (613)	72.40% (1005)
True positives of answered prompts†	653	1388
False positives of answered prompts	62	594
True positive rate‡	91.32%	70.03%

*Total number of confirmed prompts were calculated based on confirmation in the EMA survey.
†True positives were calculated based on Fitbit step data.
‡True positive rate=true positives of answered prompts divided by the sum of true and false positives.
BMI, body mass index; EMA, ecological momentary assessment; PA, physical activity; SB, sedentary behaviour.

statistics of the participants and study characteristics for both studies separately. However, nine participants in the PA study did not receive any surveys, due to syncing issues between the Fitbit device and the Fitbit app (n=7) or insufficient PA to trigger the start rule (n=2). One participant from the SB study got no surveys due to the absence of any heart rate data from the Fitbit device. Furthermore, two participants from the SB study experienced an irregular or complete absence of syncing, resulting in the loss of data on at least one day in the study. Additionally, five participants had an unexpectedly low number of surveys, probably due to disruptions with the Bluetooth connection of the Fitbit or non-wear periods. Descriptive statistics of Fitbit steps and prompts for individual participants are included in online supplemental file 5 (PA study) and online supplemental file 6 (SB study). The true positive rate (ie, proportion of surveys that were truly triggered by walking or sedentary events divided by the total triggered surveys that were answered) for the PA study was 91.32% and for the SB study was 70.03%. However, due to unforeseen technical issues in the SB study, resulting in surveys being prompted during non-events, 593 of all the 2074 (28.95%) answered surveys could not be identified as a true or false positive answer. In addition, participants confirmed being physically active in 94.16% of the EMA surveys prompted by the sensor detection of PA, and participants confirmed being sedentary in 72.40% of the surveys prompted by the sensor detection of SB. Furthermore, the PA and the SB study achieved a compliance rate of 81.22% and 79.10%, respectively. Descriptive statistics for the compliance and confirmation rates per day in both studies are presented in figure 2.

Identifying patterns concerning compliance and confirmation rates of the performed activity

PA study

In the PA study, 94% of the variance in the confirmation rate could be attributed to differences within subjects. However, due to singularity issues, the compliance rate's variance could not be calculated.

The generalised logistic mixed model did not find significant associations between time in the study and the compliance rate (exp(b): 0.92, 95% CI: 0.82 to 1.03, p=0.17). However, the odds of answering 'yes' (ie, I was indeed physically active before the survey was prompted) were significantly affected by day in the study (exp(b): 0.81, 95% CI: 0.68 to 0.97, p=0.02), with the likelihood of confirming the behaviour decreasing by 19% with each additional day in the study. In addition, the median latency between the last syncing and the start of answering the survey in the PA study was 3.13 min (IQR=15.34). Confirmation was not significantly influenced by the interaction between time in the study and latency (exp(b): 1.02, 95% CI: 0.74 to 1.43, p=0.87). However, after removing the interaction effect, a significant association was observed between latency and confirmation. Specifically, a one-minute increase in latency decreased the odds of answering 'yes' on the confirmation question by on average 20% (OR: 0.80, 95% CI: 0.72 to 0.89, p<0.01).

SB study

The ICC for compliance with SB prompts indicates that 23.40% of the variance can be attributed to differences between individuals. Similar to the PA results, the compliance rate's variance could not be calculated due to singularity issues. A generalised logistic mixed model revealed a statistically significant association between the time in the study and compliance rate (OR: 1.59, 95% CI: 1.36 to 1.86, p<0.01), with the odds of responding increasing by 1.59 times with each additional day in the study. No significant association was found between confirmation rates and study day (exp(b): 0.97, 95% CI: 0.92 to 1.02, p=0.28).

Using simulations to explore the impact of specified settings on the number of prompts

The original EMA settings resulted in a simulated median of 2.00 (IQR=1.10) and 4.26 (IQR=2.76) surveys per day per participant for walking and sedentary events, respectively. The highest number of daily surveys for walking events was obtained by setting

Figure 2 Evolution of mean compliance and confirmation rates for PA and sedentary events with corresponding CI. PA, physical activity.

Table 4 Simulations of prompt frequencies for walking and sedentary events with different EMA settings

Setting	Event duration (min)	Threshold (steps)	Minimum time interval (min)	Backwards (min)	Outlier	Prompts per day for each participant (median±IQR)
Walking events						
Original	5’	60	60’	20’	1	2.00±1.10
Simulation						
Number of steps	*5’*	80	*60’*	*20’*	*1*	1.75±0.98
	5'	100	*60’*	*20'*	*1*	1.33±1.00
Duration event	3’	*60*	*60’*	*20’*	*1*	3.14±1.57
	10’	*60*	*60’*	*20’*	*1*	1.50±1.00
	15’	*60*	*60’*	*20’*	*1*	1.25±0.79
Time interval	*5’*	*60*	0’	*20’*	*1*	4.54±3.22
	5'	*60*	30’	*20'*	*1*	2.50±1.55
Backwards	*5’*	*60*	*60’*	2’	*1*	1.60±0.67
	5'	*60*	*60'*	18’	*1*	2.00±1.12
Outliers	*5’*	*60*	*60’*	*20'*	0	1.83±0.94
Sedentary events						
Original	30'	0	120'	20'	0	4.26±2.76
Simulation						
Number of steps	*30'*	≤2	*120'*	*20'*	*0*	4.30±2.80
Duration event	15'	≤2	*120'*	*20'*	*0*	6.00±2.93
	45'	≤2	*120'*	*20'*	*0*	3.44±2.38
	60'	≤2	*120'*	*20'*	*0*	2.75±1.83
Time interval	*30'*	≤2	0'	*20'*	*0*	12.44±11.25
	30'	≤2	60'	*20'*	*0*	6.20±4.50
	30'	≤2	90'	*20'*	*0*	4.86±3.56
Backwards	*30'*	≤2	*120'*	2'	*0*	3.89±2.58
	30'	≤2	*120'*	18'	*0*	4.30±2.80

The values in italic were preserved as in the original settings of the simulations.
EMA, ecological momentary assessment.

the minimum time interval between prompts at zero minutes (resulting in a median of 4.54 daily surveys), or by shortening the duration of the event to 3 min (resulting in a median of 3.14 daily surveys). Adjusting the time span in which Fitbit could detect an event (time backwards) and the removal of one outlier did not affect the median number of surveys. The median number of surveys prompted for sedentary events increased as the interval between two surveys was shortened. The highest number of surveys, 12.44 (IQR=11.25), was achieved by setting the interval between surveys to 0 min. When adjusting the duration of the event, the highest number of surveys, 6.00 (IQR=2.93), was obtained with a duration of 15 sedentary minutes. When extending the duration of the sedentary event to 45 or 60 min, a number of 3.44 (IQR=2.38) and 2.75 (IQR=1.83) surveys were obtained, respectively. The number of surveys generated by manipulating specific EMA settings is shown in table 4.

Semistructured interviews

A total of 66 participants took part in the semistructured interviews, with 25 participants specifically addressing PA and 41 participants discussing SB.

HealthReact

Feasibility

The majority of participants (SB: n=26, PA: n=8) found answering questions on HealthReact feasible. The other participants were neutral (n=7). Only one participant required the assistance of the researchers to answer the prompts.

User-friendliness

Most participants (SB: n=25, PA: n=7) reported that HealthReact was easy to use. A few participants (SB: n=1, PA: n=2) mentioned needing some time to get accustomed to it initially, but no longer had issues afterward. However, one participant found the application difficult to work

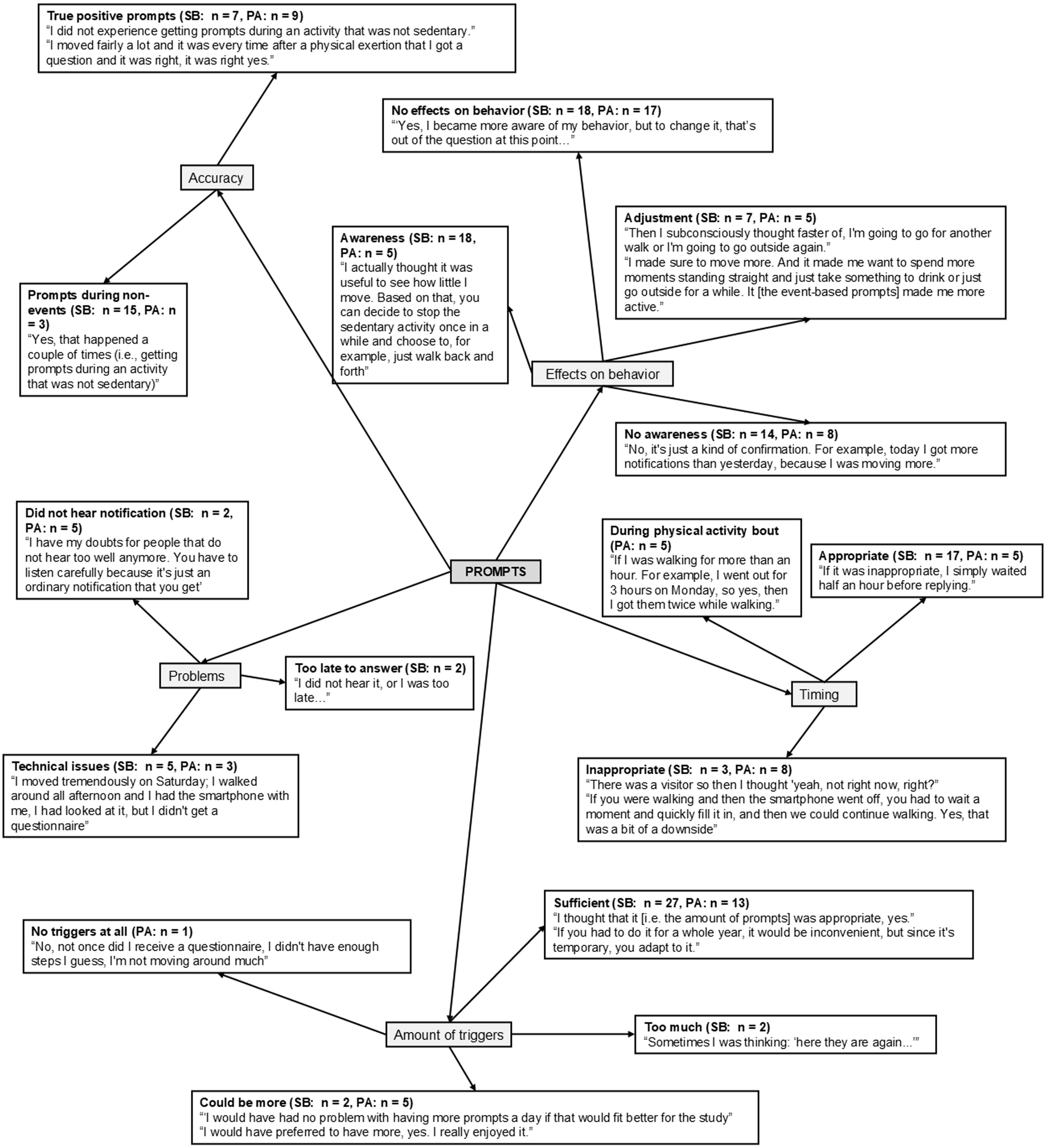

Figure 3 PEN profile: prompts. PEN profile is a structured visual representation of qualitative data, summarising participant responses and key themes. PA, physical activity; SB, sedentary behaviour.

Delobelle J, *et al*. *BMJ Open* 2025;**15**:e096327. doi:10.1136/bmjopen-2024-096327

with, and seven others had troubles while using the application (see Prompts: Problems for more details).

Prompts

Perceived accuracy

Overall, the prompts in the PA study were perceived to be accurate. However, in both studies, participants reported receiving prompts during non-events (figure 3).

Effects on behaviour

During the study, some participants became more conscious (SB: n=18, PA: n=10) of their behaviour although this study was an observational study, not aiming to change participants' behaviour. Several of them found the Fitbit data insightful, which heightened their awareness. Participant 1072 remarked, "*Now I see how many steps I take! I frequently go out for a walk, but the steps from inside the house are also counted. My total number of steps went up, which I found interesting.*" Additionally, although the researchers insisted on maintaining habitual behaviour throughout the day, some participants (SB: n=7, PA: n=5) reported actual changes in their behaviour due to the study and/or the Fitbit. For example, using the Fitbit increased the motivation of some participants to be more physically active. Participant 2037 shared, *"It made me take more walks in the garden, stand up more often, and go outside sometimes."* Conversely, most participants (SB: n=18, PA: n=17) indicated that they did not significantly alter their behaviour just because of participating in the study. For example, participant 2055 expressed being naturally motivated to stay active without relying on a Fitbit: *"I am always motivated to stay active; I don't need a Fitbit for that."*

Problems

The most commonly reported issues among participants were not hearing the prompts (SB: n=2, PA: n=5), responding too late (SB: n=2) or experiencing technical difficulties (SB: n=5, PA: n=3). However, the majority of participants indicated that they did not encounter significant problems overall.

Timing

The majority of participants (n=17) in the SB study felt that the timing of the prompts was appropriate. If a prompt was poorly timed, they simply postponed answering the survey, as they had 30 min to complete it. However, in the PA study, some participants (n=5) reported the timing of the prompts to be inappropriate. For example, they found it inconvenient to answer prompts during a walking event. Despite the end rule designed to avoid interrupting walking bouts, some participants still received prompts while being physically active.

Amount of surveys

The majority of participants (SB: n=27, PA: n=13) reported that the number of prompts was sufficient, especially for a 1-week period. In the SB study, two participants found the number of prompts too high, while two others indicated they would not mind if there were more. In the PA study, five participants expressed a preference for more prompts, as they enjoyed the experience.

Participant experiences

Smartphone usage

A significant portion of participants found smartphone usage feasible (SB: n=25, PA: n=15), attributing this to their prior familiarity with similar devices. However, varying levels of burden were associated with smartphone usage during the study. A notable challenge was the effort required to consistently carry the smartphone. Additionally, some participants (SB: n=1, PA: n=3) struggled with smartphone illiteracy, finding it difficult to navigate the device. Despite these issues, three participants from the sedentary subgroup reported that they quickly habituated to the device (figure 4).

Study duration

Opinions on the study duration varied. The majority (SB: n=29, PA: n=21) considered the 7-day duration sufficient, as it provided a comprehensive snapshot without being overly burdensome. A few participants (SB: n=7, PA: n=2) suggested that a longer duration would have been manageable and possibly beneficial. Conversely, two participants in the PA study felt the study duration was too long, particularly those who received six surveys per day.

General experiences

General experiences with the study revealed mixed feedback. One participant found managing multiple devices to be overwhelming. A few participants (SB: n=2, PA: n=3) mentioned a heightened preoccupation with the study tasks, which required continuous attention. Despite these challenges, a substantial number of participants reported no significant issues.

DISCUSSION

This study aimed to summarise lessons learnt from two sensor-triggered EMA studies on PA and SB in older adults and offer practical recommendations for future research.

Patterns in protocol adherence and the influence of methodological and technological challenges

Overall, the compliance rates in both studies align with those observed in other EMA research. A recent meta-analysis, combining self-initiated, time-based and sensor-triggered protocols in adults (>18 years) estimated an overall compliance rate of 81.9%.[24] Similarly, Wrzus and Neubauer's recent meta-analysis reported an average compliance rate of 79% across EMA studies, typically involving six assessments per day over seven days. Notably, they observed the highest compliance rates among elementary school-aged and older adult populations, with a levelling off in the oldest-old population.[22] The high compliance rates of 81.22% in the PA study and 79.10% in the SB study may thus be attributed to the study population, as older adults often achieve compliance rates above 80% in EMA studies.[33]

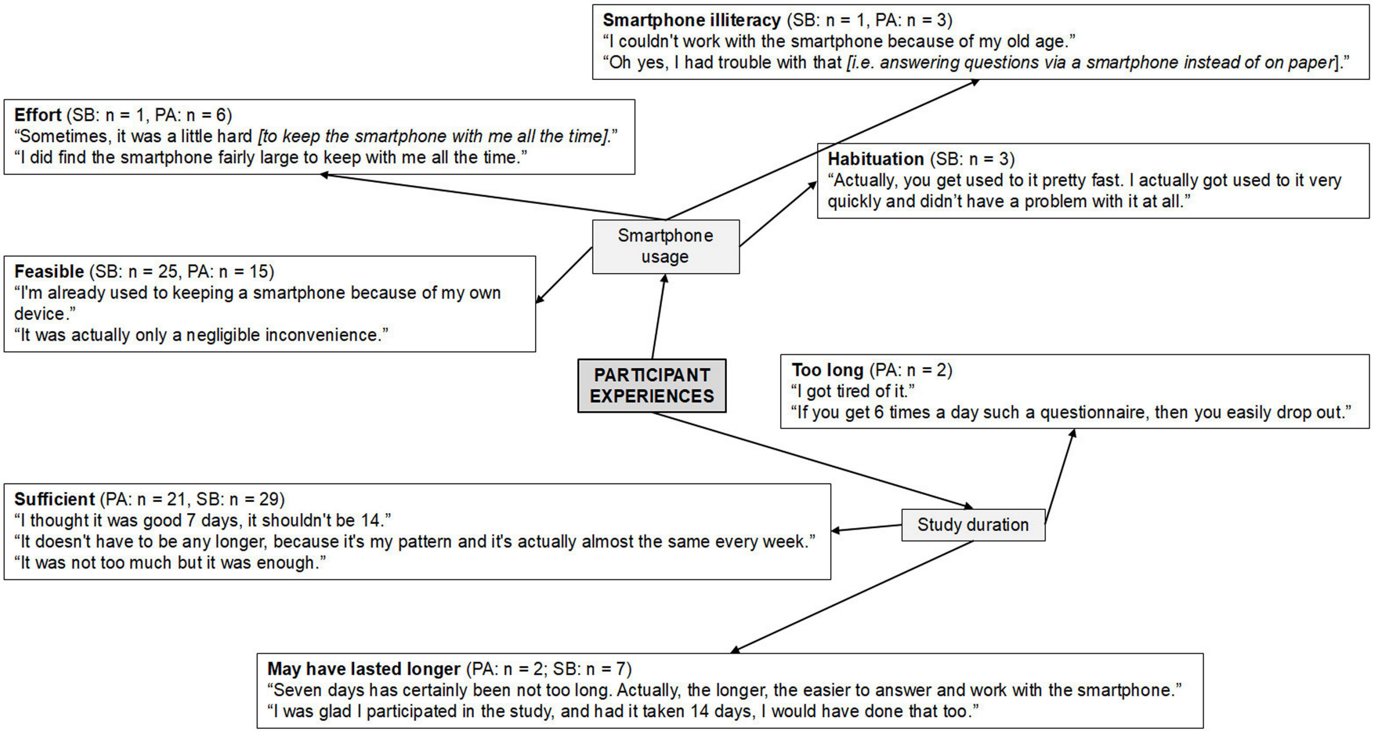

Figure 4 PEN profile: participant experiences. PEN profile is a structured visual representation of qualitative data, summarising participant responses and key themes. PA, physical activity; SB, sedentary behaviour.

In the PA study, 91.32% of the EMA surveys were correctly prompted and responded to, whereas in the SB study, a true positive rate of 70.03% was obtained. The low true positive rate in the SB study was due to a technical issue that triggered surveys even when heart rate data were absent, causing some surveys to be prompted during non-wear periods. In addition, wrist-worn Fitbits are not the gold standard for capturing SB and may lead to misclassification of standing and sitting time, which could also slightly explain the lower true positive rate. However, a Fitbit validation study demonstrated that specific cut-off values can detect prolonged bouts of SB with high sensitivity and specificity when compared with ActivPAL.[29] However, these cut-off values were not applied in the current study (since the calculations were not available at the beginning of the study), but are useful for future studies. Furthermore, descriptive statistics of the SB study revealed that the confirmation rate (ie, the proportion of confirmed behaviour by the participants) was 72.40%. Due to the habitual nature of SB,[34] participants may not always recognise certain inactive periods as sedentary, impacting their reporting. In addition, sitting is often a secondary activity associated with other tasks, leading to reduced awareness of their sitting behaviour.[35] However, in the current studies, surveys were terminated if participants did not confirm the confirmation question. Some participants may have intentionally denied the confirmation question to save time or because they were unwilling to answer the surveys, although this remains speculative. In addition, the high true positive rate of 91.32% and high confirmation rate of 94.16% for walking events (which is a rather planned, conscious behaviour) indicate that the prompts effectively corresponded with the moments when participants were actually physically active, and participants’ perceptions aligned with this finding. However, participants in the PA study received fewer EMA surveys, which may have reduced participant burden and decreased the likelihood of early survey discontinuation by denying the confirmation question. Furthermore, the low confirmation rate in the SB study compared with the PA study may reflect socially desirable responding, as participants might find it more appealing to report PA rather than indicate they were sitting. Sensor-triggered EMA surveys may, therefore, provide more objective and consistent recording of routine or less noticeable activities, compared with self-initiated EMA, which risks under-reporting, as participants must actively report when an event occurs.[15]

The analysis of the patterns of compliance and confirmation rates revealed significant patterns that provide insights into participant behaviour and the reliability of our sensor-triggered EMA data. In the SB study, compliance rates showed a strong increase over time. This trend might be attributed to the fact that older adults may require some time to become accustomed to smartphone usage, as indicated by several participants during the interviews. Conversely, in the PA study, no significant relationship was found between the time in the study and compliance rate. In the SB study, the confirmation rate remained stable over time, aligning with findings from a previous study that also reported no decline in response quality as time progressed.[36] However, in the PA study, participants increasingly reported not engaging in PA as the study progressed. In addition, an increased latency between the last syncing and survey response resulted in a significant drop in confirmation rates, likely due to recall bias. Minimising delays in survey prompts is important to ensure surveys are associated with the participant's behaviour, which helps maintain high confirmation rates. While reducing these delays might be possible in the future, it depends on the technical limitations of wearable devices like Fitbit, which use periodic syncing (eg, every 15 min) to balance battery life and data transmission. Real-time syncing could mitigate delays, but it poses challenges such as reduced battery life, increased data bandwidth and server load.

By simulating the expected number of prompts under various conditions using Fitbit data, valuable insights are provided into how specific EMA settings affect the frequency of survey prompts during both walking and sedentary events. For walking and sedentary events, reducing the minimum interval between surveys or shortening the event duration led to an increase in the number of daily prompts, which is similar to findings from another sensor-triggered EMA study.[37] However, maintaining a minimum interval between surveys may be crucial to avoid repeated surveys for the same activity, which ensures a representative overview of activities and their determinants throughout the day. This also helps to minimise participant burden, as an excess of surveys could lead to lower participation rates and decreased response accuracy due to fatigue.[14 19 38] Furthermore, for sedentary events, adjusting the step count threshold to ≤2 steps per minute—yielding optimal sensitivity and specificity rates[29]—did not impact the median number of daily surveys. The simulations further indicated that excluding outliers and reducing the maximum time backwards led to a slight decrease in the number of prompted surveys. However, extending the time span to 18 or 20 min backwards could prompt surveys for behaviours that were performed some time ago, which may decrease confirmation rates and render them less relevant to the event of interest and potentially introduce recall bias. In addition, the simulation, which replicated the original study settings, predicted a median of two daily surveys for walking events and four for sedentary events. However, the real-life prompted surveys were one and six, respectively. This discrepancy may be attributed to the fact that the two-minute inactivity end rule was not applied in the simulations, and consistent syncing was assumed, which may not reflect real-world conditions. Furthermore, the technical issue experienced in the SB study resulted in the increased number of prompts in the real-life study compared with the simulations. More detailed recommendations for both PA and SB individually can be found later in the discussion section (under 'Recommendations').

EMA platform

When conducting sensor-triggered EMA, several technological and methodological decisions have to be made.[39] First, researchers have to determine which software platform to use. Each platform presents distinct advantages and limitations. In this study, HealthReact was used. HealthReact offers the possibility to serve as an mHealth platform for real-time data collection and to trigger JITAI.[40] HealthReact is currently being used in various research studies focusing on PA, SB and eating behaviour research.[41–44] This software platform combines an EMA platform with third-party sensors featuring an open API to access sensor data in real-time. While various accessible and inexpensive sensors in the form of commercial wearable devices such as activity trackers are available, these wearables are not consistently validated for measuring short bouts of PA and SB. Furthermore, continuous internet connection is necessary to sync data between the activity tracker and EMA platform. HealthReact supports diverse data sources, including wearable devices (eg, Fitbit, Garmin and Apple Watch), and sensors for glucose, heart rate, air pollution, weight and Global Positioning System (GPS). In addition, researchers could monitor enrolled participants through HealthReact, viewing the timing and frequency of prompts for each participant. This allowed researchers to identify and address potential technical issues occurring at the smartphone level, often without participants' knowledge. For instance, sometimes participants unintentionally altered Bluetooth settings, powered off the device or enabled flight mode. By tracking prompts in HealthReact, researchers could proactively contact participants when issues were detected, helping to resolve problems early and minimise data interruptions.

Other software platforms also exist, such as (1) smartphone apps using built-in sensors and (2) integrated solutions merging the EMA platform with proprietary sensors and (3) semiautomated, interactive monitoring algorithms that send prompts based on activity thresholds derived from accelerometer data.[21] The first option demands good battery life of smartphones and offers limited flexibility in setting triggering scenarios. The second option is expensive and restricted by the range of sensors provided by the vendor (eg, Movisens). This method has been successfully implemented in previous research using SB-triggered EMA, demonstrating its feasibility.[20] The third option necessitates researchers' involvement in monitoring and triggering diaries, which may introduce delays or inaccuracies, making it less suitable for larger samples. Furthermore, in literature, no overview exists of sensor-triggered EMA platforms and accompanying applications, explaining their methodological aspects, advantages and disadvantages. Further research is needed to provide a detailed overview of existing sensor-triggered EMA platforms, along with an analysis of their pros and cons.

Recommendations

Despite its potential and although the interviews generally showed a positive user experience, several challenges emerged in the current studies. While the majority of the interviews indicated high feasibility and user-friendliness, some participants reported that they did not hear the notification, resulting in missed EMA surveys, while others had insufficient time to complete the questions or experienced technical difficulties. For instance, 10 participants in the PA study and two in the SB study experienced irregular or complete lack of syncing. Additionally, almost all participants were provided with a study device. Only a handful of the first participants used their own smartphone. However, since HealthReact was not compatible with all smartphones and to avoid further technical issues, we decided to provide recent study devices for every participant. Moreover, some participants had no prior experience with smartphones. Although researchers offered a brief training session, including a test questionnaire on HealthReact to familiarise participants with basic smartphone handling and verify question clarity, some participants mentioned that they still needed time to get accustomed to the application. A recent compliance study incorporating data from the current study supports these findings, showing higher compliance rates among older adults already familiar with smartphones.[26] An additional user-friendly manual covering essential smartphone skills with clear instructions and pictures (eg, turning the device on, checking Wi-Fi or Bluetooth settings) may be a valuable resource for future studies. This would allow participants to review technical information at their own pace and reduce potential overwhelm during the training session. Furthermore, it could improve participants' sense of self-empowerment and confidence in managing the technology independently. In addition, a screening process to assess participants' comfort with technology, their familiarity with wearable devices, and their ability to manage the intensity of an EMA study could be beneficial prior to their participation. For example, brief interviews during recruitment could help identify participants who might find the study burdensome. Moreover, providing ongoing technical support and regular check-ins to gather feedback during the study can help address participants' concerns and make real-time adjustments. Finally, researchers should be aware that participation in the study might make participants more conscious of their behaviour, potentially leading to changes towards more desired patterns.[38] This phenomenon, known as 'EMA reactivity',[45 46] was observed in our study and may be attributed to two factors. First, the feedback display on the Fitbit device may have influenced participants, who reported becoming more aware of their behaviour due to the visibility of their step counts. Second, the nature of the event-based EMA, with prompts triggered by specific behaviours such as prolonged sitting or walking, could also have contributed to increased awareness. Although a few participants indicated they went for more walks or paid closer attention to their sedentary time, the majority did not report any changes in their behaviour. Researchers using sensor-triggered EMA should therefore be mindful of potential reactivity, even if its effects may be limited to a small subset of participants. Another potential approach for studying PA and SB using sensor-triggered EMA could involve sending surveys when participants are neither physically active nor sedentary (ie, a mixed-sampling strategy of triggering during events and non-events). This approach could also help researchers better understand the determinants and consequences of these behaviours. Additionally, by incorporating randomised prompts rather than solely relying on sensor-triggered EMA, this method ensures data collection even among individuals with lower PA levels, eliminating the need to exclude participants based on their PA engagement.

In addition, future EMA studies, particularly those using sensor-triggered designs, would benefit from the development of specific guidelines to ensure consistency and transparency. Existing frameworks, such as the Checklist for Reporting Ecological Momentary Assessment Studies (CREMAS) checklist,[47] could be expanded to include aspects unique to sensor-triggered EMA, such as a comprehensive description of the hardware and software used, the EMA platform, the rules for triggering events and the rationale for the chosen sampling design. Such tailored guidelines would enhance the reproducibility and comparability of sensor-triggered EMA studies. Finally, it is important to validate wearable devices for use in sensor-triggered EMA to account for variability across devices and ensure applications in future research. Furthermore, it is also essential to consider the capabilities of the EMA platform and potential delays in real-time data transfer, such as the syncing delay between a wearable and its server, which could affect the timing of event detection.

Physical activity

Based on the current study and the simulations we conducted, recommended settings for prompting for walking events in older adults are as follows. First, using a threshold of at least 60 steps/min to prompt walking events is recommended, as it is a feasible threshold that yields a sufficient number of daily surveys and can be considered sustained walking.[29] Given that the median number of daily surveys is already low (one per day), and increasing the threshold to 80 or 100 reduces the median number of daily surveys, 60 steps/min seems optimal for older adults. However, this rate does not reach the intensity of moderate PA, which is approximately 110 steps/minute.[48] In addition, relying solely on step counts excludes the possibility of prompting surveys for other types of PA, such as muscle strengthening, balance and coordination exercises. However, since Fitbits' 'active minutes' are not valid for detecting short bouts of moderate to vigorous PA,[19] step counts, rather than 'active minutes', are recommended to prompt EMA surveys. Alternatively, EMA surveys could be prompted based on heart rate, but setting a heart rate threshold is challenging, as events could also be prompted by stress or anxiety rather than PA.[49] Furthermore, such EMA protocols are currently lacking in literature. Second, extending the duration of an event reduces the median number of daily surveys, especially in older adults who are a relatively inactive population. Therefore, prompting an EMA survey after just five minutes of walking is recommended for researchers investigating short bouts of PA, which is similar to findings from another sensor-triggered EMA study.[37] If the research focus is on longer bouts of PA, extending the overall study duration could help ensure sufficient data are collected to address the research objectives. Third, extending the time span to 20 min backwards could prompt surveys for behaviours performed much earlier, reducing the validity of the study and the confirmation rate. Therefore, setting max backward at two minutes is recommended and may yield more ecologically valid data. Fourth, while end rules can prevent the interruption of PA by an EMA survey, they can result in missed events if the end rule is too strict. For example, a walking event might be missed if the end rule requires inactivity of less than 10 steps per minute for two consecutive minutes, but the participant keeps moving at about 20 steps per minute, which would be comfortable enough to answer the survey. Furthermore, the effectiveness of the end rule is influenced by the maximum time interval to detect an event in the past. In our study, this interval was set to 20 min, meaning that the HealthReact server remains on standby until the end rule is met within this time frame. As a result, even if a walking event is followed by two minutes of inactivity, these two minutes can occur anywhere within the 20-minute window, potentially allowing the participant to resume walking before the prompt is triggered. This diminishes the impact of the end rule and may lead to EMA prompts being sent during ongoing walking events. Indeed, some participants reported in the interviews that they received EMA surveys during walking events, which they found inconvenient. To prevent this and ensure that prompts are only sent when an activity bout has truly ended, end rules should be applied with a shorter time backwards interval. Furthermore, defining an end rule is challenging because a threshold of ≤60 steps per minute may be considered a non-event but could still represent light PA. Fifth, although simulations in this study showed no impact of outliers on the number of daily prompted surveys, considering outliers could be useful in specific situations, such as when a participant stops at a traffic light. However, allowing an outlier in a five-minute PA event may not be valuable if researchers are interested in sustained walking. Sixth, the majority of the participants found a 7-day measurement period feasible and did not mind a longer duration.[19] Extending the study period may provide more profound insights into the participants' behaviour and experiences. Seventh, depending on the research questions, it may be beneficial to exclude participants who do not engage in PA. For predictive or causal research questions, a mixed sampling strategy is recommended.[50] In contrast, for descriptive research questions, excluding participants with insufficient PA may be necessary, as they would never receive a sensor-triggered EMA survey and, therefore, would not be represented in the study results.

Sedentary behaviour

In this study, step data were used to prompt surveys for sedentary events.[29] An alternative method to prompt surveys could involve using 'sedentary minutes' tracked by the Fitbit. Comparative studies have evaluated this Fitbit metric against activPAL[51] and GT3X+[52] devices. These studies indicated that Fitbits' measures are comparable to these devices. However, they only assessed daily sedentary time and did not investigate shorter time periods, which are crucial for sensor-triggered EMA.

The duration of the event of interest should be carefully determined based on the research question. The longer the event duration, the fewer surveys will be prompted. For instance, a shorter event lasting for 15 min could prompt a median of six surveys per day, while an event lasting one hour might result in only three surveys per day. When defining bout durations based on the research question, these differences in prompt frequency should be considered, as a longer study period may be necessary to ensure adequate statistical power, particularly when fewer surveys are prompted daily. Moreover, the desired distribution of surveys should also be carefully considered. Removing the time interval between survey prompts in simulations more than doubled the number of surveys prompted for a 30 min event. However, prompting multiple surveys within the same sedentary bout may be undesirable, especially when studying distinct sedentary events. Thus, maintaining a time interval between prompts can be advantageous for certain research questions. Additionally, depending on the desired maximum number of surveys per day, researchers may want to adjust this interval to ensure that surveys are distributed evenly throughout the day.

In this study, the study duration for each participant was seven days, based on the typical duration of other EMA studies that lasted between one and ten days.[19] However, in some of the participants included in our study, data collection extended beyond the planned seven days because researchers were unable to conduct the final home visit on the exact day following the last scheduled day. The fact that participants continued to respond to the surveys, even though they were explicitly instructed to do so for only seven consecutive days, suggests that they may not have minded a longer study duration. This hypothesis is supported by the qualitative interviews, in which most participants expressed that they would be willing to participate in a longer study if it would benefit the research.

This study employed a continuous sensor-triggered approach, allowing participants to receive survey prompts throughout the entire study period whenever the event of interest occurred. While this method enables comprehensive data collection, it can result in a high number of daily surveys, potentially increasing participant burden.[19 53] When researchers are interested in measuring over longer periods, such as several weeks or months, this approach would be too burdensome for participants. To mitigate this burden, an EMA burst design could be a possible alternative for some studies. Instead of conducting continuous assessments over an extended period, participants are asked to complete several assessments within a shorter, concentrated timeframe. For example, participants might be involved in the study over several weeks but only receive surveys on specific days within that period. This approach allows for data collection spread out over a longer time frame while minimising the frequency of surveys over the total study period.[25 54]

To optimise study validity, the maximum timespan that HealthReact looks back should be set as short as possible. While a two-minute 'max backwards' setting is recommended, it may slightly reduce the number of survey prompts compared with longer settings.

In contrast to the PA study, no end rules were set for the SB study. This was done intentionally. We assumed that by prompting a survey during a sedentary episode, participants would still be able to easily respond while the episode was ongoing. This was also confirmed by the qualitative interviews. However, if the researcher would be more interested in specific factors that can only be measured immediately after the episode, an 'end rule' could be opted for. This might be relevant in research questions related to, for instance, interrupting sitting behaviour.

Strengths and limitations

This study has some notable strengths. First, this study employed a sensor-triggered method to prompt surveys based on PA and SB, providing valuable insights in this field. Second, the study's mixed methods approach, integrating both qualitative and quantitative data, provides a more comprehensive understanding. Third, combining the lessons learnt from two separate studies focusing on PA and SB enhances the insights gained on sensor-triggered EMA studies in general and sheds light on the recommendations specific to these behaviours.

However, the study also demonstrates several limitations. First, since the current study was conducted among older adults, the lessons learnt may not be applicable to all populations. Factors such as varying thresholds for PA intensity and cadence, PA and SB patterns, disparities in technological literacy and sensory limitations (ie, hearing loss, tremor, visually impaired) could impact the methodological choices for conducting sensor-triggered EMA in other populations. Nevertheless, given the limited literature on methodological considerations for sensor-triggered EMA studies for PA and/or SB in all populations, this study could provide valuable insights for researchers aiming to conduct sensor-triggered EMA studies in other populations as well. Second, participants of both studies were recruited through purposive convenience sampling, potentially limiting the generalisability of the study findings. However, efforts were made to ensure a heterogeneous sample by considering sociodemographic factors such as age and gender. Third, there were issues with prompting surveys in the study focusing on SB due to a bug in the HealthReact application, resulting in a smaller dataset and possibly compromising the reliability of the sensor-triggered prompts. Fourth, in some models (ie, the model for compliance rate in the PA study and the model for confirmation rate in the SB study), the random effect for days was removed to avoid overfitting, which limited our ability to fully differentiate between within-person and between-person variability in adherence. Future research with larger sample sizes or alternative modelling approaches could better capture temporal fluctuations in adherence within individuals. Fifth, we acknowledge limitations regarding the trustworthiness of our qualitative findings. Specifically, we did not employ member checking or researcher triangulation, which may have impacted the validation of our findings and the interpretation of participant perspectives.

CONCLUSIONS

This study highlights the potential of sensor-triggered EMA as a valuable tool for capturing real-time data on PA and SB among older adults. The high compliance rates (over 79%) in both studies demonstrate good adherence to the EMA surveys. Qualitative insights further indicate that most participants found the application user-friendly and feasible to use, with overall positive feedback regarding their participation in the study. In the PA study, confirmation and true positive rates were notably high, indicating that the EMA surveys were prompted accurately after walking events. Conversely, the SB study showed lower true positive and confirmation rates, likely due to technical issues and discrepancies between participants' self-perceptions and device-based Fitbit measurements, respectively. Practical recommendations (eg, specific settings to prompt EMA surveys) for future sensor-triggered EMA studies focusing on PA and SB events among older adults were provided. However, significant challenges remain, including a negative impact of latency on survey response, technical issues, notification timing and EMA reactivity, which must be addressed to improve protocol adherence and the validity of future findings on older adults' health behaviours in EMA research.

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Contributors JD, EL, SC, DVD and TV designed the research question. EL and JD collected the data for the SB and PA study, respectively. RC and JK contributed to data collection and provided technical support as needed throughout the study. JD, EL, TV and JK cleaned the data and performed the analysis. EL and JD wrote the first draft. JD, EL, TV, SC, JVC and DVD read, provided feedback and approved the final manuscript. JD and EL contributed equally to this paper. DVD is the guarantor. ChatGPT was used to academically rewrite sentences.

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Patient consent for publication Consent obtained directly from patient(s).

Ethics approval This study involves human participants and the studies were conducted in accordance with the Declaration of Helsinki and approved by the Ethical Committee of the Ghent University Hospital (BC-09944). All participants provided informed consent before inclusion in the studies.

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