A just-in-time adaptive intervention to enhance physical activity in the SMART*FAMILY*2.0 trial.

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Abstract

Just-in-time adaptive interventions (JITAIs) are a promising technology-based approach for health behavior change. This examination aimed to evaluate whether a JITAI after a period of inactivity can enhance physical activity in the subsequent hour depending on whether the JITAI has been answered ("engaged" condition) compared to when the trigger was not answered ("not engaged" condition). Data of the three-week intervention period of the SMART*FAMILY*2.0 trial was used for analysis. A total of 80 participants (n = 47 adults, 23 female; n = 33 children, 15 female) with 907 JITAI triggers were included in this examination. A JITAI was sent when the participant has been inactive for at least 60 minutes as indicated by accelerometry. Two multilevel models were calculated for metabolic equivalents (MET) and step count with measurements (level 1) nested in participants (level 2) under consideration of the covariates weekday/weekend, time of the day, and adult/child. Results indicated significantly higher MET ($\beta = 0.08$, $p = .014$) and step ($\beta = 0.08$, $p = .022$) counts in the subsequent hour for the engaged condition compared to the not engaged condition within-persons (level 1). Engagement with the JITAI implemented in the SMART*FAMILY*2.0 trial yielded promising results concerning physical activity enhancement in the subsequent hour. Here, the inclusion of further constraining factors like the availability of the participant or the inclusion of affective and contextual variables into the design of a JITAI might enhance the engagement in future studies.

Keywords: Physical activity, Mobile Health, individual tailoring

One important aspect which is linked to metabolic health in children, adolescents (in the following referred to as children), and adults is the avoidance of prolonged phases of physical inactivity like deskwork or watching TV with an energy expenditure of or below 1.5 metabolic equivalents (MET) (Healy et al., 2008; Tremblay et al., 2011). In the context of health benefits, the reduction of prolonged inactive phases is positively associated with physiological health markers like Body Mass Index, waist circumference, and plasma glucose levels in several studies (Carson et al., 2014; Dunstan et al., 2012; Healy et al., 2008). In modern society, values of physical inactivity are rising (Bull et al., 2020; Owen et al., 2010) and effective ways to change health behavior throughout the lifespan are needed.

A promising option to deliver cost-effective interventions with a large coverage that aims to break inactive phases is digital interventions (Vandelanotte et al., 2016). Here, mobile health (mHealth) interventions are described by the World-Health-Organization as “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices” (World Health Organization, 2011) are especially promising due to increased access to digital devices worldwide (Statista, 2022). One key facet to designing effective mHealth interventions in the context of physical inactive phases is the individual tailoring of the interventions to correspond to the participant's behavior (Fiedler et al., 2020; Wunsch et al., 2022). A special case of individual tailoring are just-in-time adaptive interventions (JITAIs) which can be used to interrupt physical inactive phases and enhance PA by providing tailored messages or reminders for healthy behavior in these moments (Hardeman et al., 2019). JITAIs have the potential to automatically intervene when people are most prone to unhealthy behavior or have an opportunity to engage in healthy behavior and adapt these interventions to tailoring variables like user preferences or sensor input (for an overview see

Nahum-Shani et al., 2018; Wunsch et al., 2022). For a digital intervention to be defined as JITAI the following requirements need to be fulfilled: 1) correspond to real-time needs; 2) adapt to input data; 3) be system-triggered. This can be extended for the enhancement of effectivity by 4) being goal-oriented; and 5) be customized to user preferences (Wunsch et al., 2022). In this regard, decision points refer to the points in time when a JITAI can be triggered, decision rules refer to the rules which determine if a JITAI is triggered at a decision point, intervention options refer to the possible actions of the JITAI at a decision point, and tailoring variables refer to sensor- or user-input that is used for adaptation. These depict the key features to design JITAIs (Nahum-Shani et al., 2018). Here, the choice of adequate decision points and rules for opportune moments present the main challenges in JITAI design. These moments can be defined as times when participants can engage in healthy behavior or avoid unhealthy behavior. This is especially important since too many untimely triggers can affect user satisfaction while not enough triggers might not lead to the desired health behavior change or even have adverse effects by promoting engaging with behavior in unintended moments (Gonul et al., 2019). This adaptation of interventions is getting more sophisticated and promising due to technological advances in PA research to which smaller and more powerful accelerometers contribute greatly (Burchartz et al., 2020). A recent systematic review by Baumann and colleagues (2022) confirmed the importance of individualization regarding the effectiveness of mobile physical activity interventions for children.

Previous studies on JITAIs in the context of PA show promising results for a daily accumulated PA in adults (Rabbi et al., 2015) and that sending higher frequented JITAIs per day (after 30/60 minutes of inactivity compared to 120 minutes) was associated with more frequent walking breaks in daily life in adults with overweight (Thomas & Bond, 2015). Research in children with overweight also indicates benefits from JITAIs concerning physical activity promotion (Spruijt-Metz et al., 2015). Feasibility studies point to a high user acceptance and preliminary evidence for the effectiveness of JITAIs while more detailed evaluations are needed (Hardeman et al., 2019). Overall, there is a lack of studies evaluating the association of user engagement with JITAI triggers regarding PA under free-living conditions or during mobile health interventions (Hardeman et al., 2019). Previous studies either did not investigate user engagement, such as timely answering the trigger by clicking on the notification, or focused on e.g. days of smartphone use (Hardeman et al., 2019). Here, evaluating the momentary effect of engagement directly after the trigger occurs is especially relevant as the JITAI is to be triggered in opportune moments for behavior change and a timely response is assumed to be important (Wunsch et al., 2022). The consideration of different aspects of PA is important, to distinguish between the implications of JITAIs for health behavior change (Silfee et al., 2018). These can be device-based measured steps as a measure which is used by most people with fitness trackers or smartwatches as a daily goal and MET as an indicator for PA intensity.

Therefore, the current examination aimed to evaluate the effectiveness of engaging with a JITAI after a prolonged phase of inactivity (>60 minutes) on device-based measured MET and step counts in the hour following the trigger during a real-time intervention setting over 21 days in both children and adults.

It was hypothesized that device-based measured step and MET counts in the 60 minutes following the answering of a JITAI trigger ("engaged" condition) were significantly higher within-persons than step and MET counts in the hour where a trigger has been sent but was not answered within 60 minutes ("not engaged" condition).

Additionally, the persistence of the effect for 90 and 120 minute time frames and the between-person effects were exploratively examined. The relevance of the stated reason for the previous period of inactivity has been explored descriptively.

Methods

Transparency and Openness

Data for the current within-person study origins from the SMART*FAMILY* study. The detailed study protocol of the SMART*FAMILY* study can be found elsewhere (Wunsch et al., 2020). The International Registered Report Identifier (IRRID) for the SMART*FAMILY* study is DERR1-10.2196/20534 and the protocol for the current examination has been pre-registered and uploaded to the open science framework along with the data and analysis code (Fiedler et al., 2021, July 15). Full ethical approval was obtained from the University of Konstanz (for the consortium SMARTACT) as well as from the Karlsruhe Institute of Technology for SMART*FAMILY*. All participants provided written informed consent. The trial was conducted in accordance with the Declaration of Helsinki.

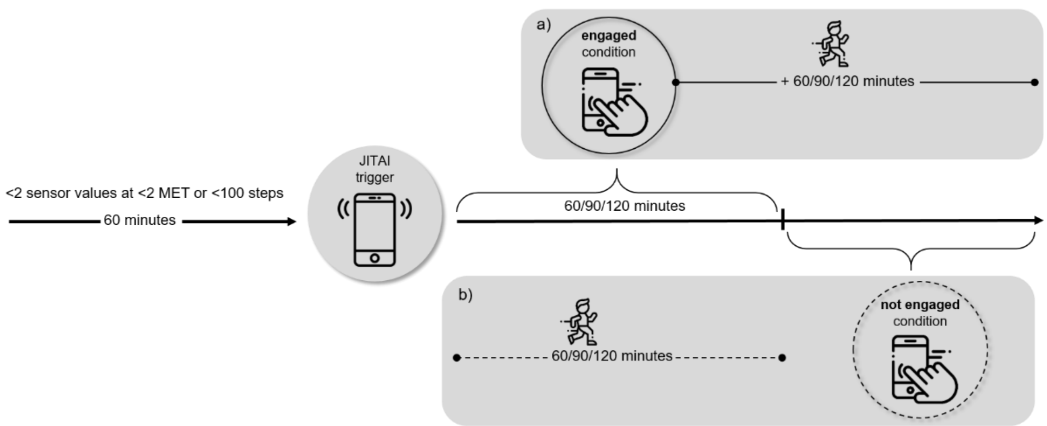
Participants and Procedure

Families including at least one parent and at least one child who was 10 years of age or older and who were living together in a common household were eligible for the main study. Families have been cluster-randomized into an intervention group and a control group. All measurements were conducted during regular school times to avoid influential behavioral differences between school times and holidays. Both groups participated in a baseline measurement of one week, followed by a three-week intervention/waiting period, a one-week post measurement, and a follow-up questionnaire four weeks after the post measurement. The intervention duration was set to three weeks to allow for measurements from baseline to post to take place between public school holidays which are usually six weeks apart. Previous mobile health studies found significant behavior change effects for interventions with a duration of three weeks and shorter (Fukuoka et al., 2010; Garde et al., 2015; Sirriyeh et al., 2010), and three weeks is a common duration for JITAIs (Hardeman et al., 2019). Each participant was provided with a smartphone and simultaneously wore a 3-axial accelerometer placed at the hip which corresponded with the smartphone via Bluetooth Low Energy during the intervention period. Participants only had access to the preinstalled SMART*FAMILY*2.0 application (app) on the provided smartphone. The app intervention aimed to support the three psychological needs competence, relatedness, and autonomy which are the foundation of the self-determination theory (Ryan & Deci, 2000). Several behavior change techniques like providing information, and goal setting for weekly steps, and moderate-to-vigorous PA goals were included in the app (Wunsch et al., 2020). Additionally, participants received ecological momentary assessments (i.e. assessing sleep quality and core affect with 4 single item questions) to collect data as part of the study design and an event-based JITAI after a period of physical inactivity longer than 60-minutes. All participants were instructed on app use by a researcher from the SMART*FAMILY* study and were provided with a booklet including precise instructions on how to use the app along with troubleshooting. Participants received a 40€ (US $46.8) online shopping voucher and an activity tracker for every child of the family after completing the three assessments of the main study. Participants were not compensated for answering the JITAI and related questions within the app. Power analysis was conducted a priori and resulted in a required total sample size of $N = 156$ participants to detect a small-to-medium effect for the main trial (Wunsch et al., 2020). Overall, $N = 192$ participants were included in the SMART*FAMILY*2.0 trial, indicating sufficient power.

Only data from the intervention group (*N* = 98, 52% adults) during the three-week intervention period has been included for the current examination. Here, the secondary data analysis focuses on the effect of engaging vs not engaging with the JITAI trigger on subsequent PA during the 60/90/120 minutes following the trigger in a within-person design (see figure 1).

Figure 1

Illustration of 60/90/120-min time windows summarizing physical activity data (step count and METs) when (a) the JITAI trigger was answered within the subsequent 60/90/120 minutes ("engaged" condition) or (b) when the JITAI trigger was not answered within this time window ("not engaged" condition)



Measurements

Questions about age, sex, and anthropometry were included in the questionnaire of the main study at the end of the baseline measurement (Wunsch et al., 2020).

Accelerometry

Step count and MET were continuously recorded by 3-axial accelerometers (Move 3/Move 4, movisens GmbH, Karlsruhe, Germany). The accelerometers were small-scale (62.3 mm x 38.6 mm x 11.5 mm) and light-weight and were attached by a clip or at a belt to the right hip. Raw data was sampled at an input frequency of 64 Hz and stored on an internal memory card. The accelerometers have been shown to accurately detect step counts (Anastasopoulou et al., 2013) and to validly estimate energy expenditure (Anastasopoulou et al., 2014). Participants were instructed to wear the accelerometer during wake time for the whole intervention period of 21 consecutive days and were told to remove the sensors during showering, swimming, or during contact sports. If participants did not wear the sensor but participated in any exercise, they were instructed to manually record the duration and intensity of the exercise in the SMART*FAMILY*2.0 app (data not included in this examination).

Just-in-time adaptive intervention

The JITAI was based on the behavior change technique "Teach to use prompts/ cues" (Michie et al., 2011) which improves the psychological need for the competence of participants as described in the study protocol (Wunsch et al., 2020). We used an event-contingent scheme with JITAI triggers which were sent via the SMART*FAMILY*2.0 app when the participant has been detected to be inactive by the accelerometer for more than 60 minutes which was a decision rule based on tailoring variables. More specific, if neither <2 sensor values at >2 MET nor 100 steps were registered on the accelerometer, sensor input lead to a decision point. These thresholds were chosen based on previous research pointing out that interrupting inactive phases for at least one minute is associated with health benefits (Carson et al., 2014; Dunstan et al., 2012; Healy et al., 2008) while 60 minutes instead of a shorter period were chosen to lower participant burden. The 60-minute time window following the trigger was chosen to correspond to the minimal frequency of decision points as triggers could only occur every 60 minutes. Triggers regarding inactivity were inhibited for the remaining day if the participant reached at least 60 minutes of moderate-to-vigorous PA on a respective day corresponding to PA guidelines for children (Bull et al., 2020). Furthermore, the trigger only occurred if the participant indicated wakefulness by pushing the wake-up button on the app, if there were at least 50 of 60 minutes of recorded sensor values within the past hour, and if there has been no manually adjusted activity for the past 60 minutes within the app. These represented further decision rules. The JITAI was a simple notification stating: ‘You didn't move between 9:00 and 10:14. You should start moving!‘ which has been used in a similar vein by previous research (Gouveia et al., 2015; He & Agu, 2014; Pellegrini et al., 2015). Additionally, a single item about the reason for the inactivity with the four possible answers ‘I engaged in PA but did not wear the sensor‘, ‘I did not have any time‘, ‘I did not feel like doing that‘, ‘I did not feel well‘) and a mood assessment via ecological momentary assessment (not included in this examination) was sent. The JITAI notification prevailed until it has been answered and disappeared at midnight if it has not been answered.

Data analysis

Regarding the PA data, raw data has been summarized in 60-second epochs using the software DataAnalyzer, version 1.13.16 (movisens GmbH, Karlsruhe, Germany) and was processed by algorithms into step and MET counts per minute and non-wear time. MET values were calculated based on activity class which in turn is based on acceleration and barometric signals and determines the estimation model. Then, movement acceleration, altitude change, and demographics were combined in the model for the MET estimation (Härtel et al., 2011). Afterward, PA and JITAI data have been merged using RStudio (R Core Team, 2021; RStudio Team, 2021). Here, rolling sums for 60, 90, and 120 minutes of the PA data summarized the 60/90/120 values per minute after the trigger. These variables were then matched to the timestamp when the trigger has been sent to the participants if the JITAI has not been answered within 60/90/120 minutes. This was defined as the "not engaged" condition as the participants did not answer the trigger. If the participants engaged with the app by clicking on the notification and answering the follow-up questions within 60/90/120 minutes, this was defined as the "engaged" condition and matched to the timestamp when the trigger has been answered by the participant (see figure 1). PA data has been considered valid if the sensor has been worn for at least 80% of the respective 60/90/120 minutes. To avoid overlapping periods, the time between the condition ("engaged" or "not engaged") and the condition of the following trigger has been checked and the second trigger has been deleted if the time between the conditions was less than 60/90/120 minutes.

Statistical analysis

Different packages of R (R Core Team, 2021) and RStudio (RStudio Team, 2021) were used for all analyzes. The package 'ggplot2' was used for visualizations (Wickham, 2016). Multilevel models were calculated using the package 'lmerTest' (Kuznetsova et al., 2017) with the time of the measurement (level 1) nested in participants (level 2) to identify the within- and between-person effects concerning the research question. The result tables of the regression analyses were generated using the package 'sjPlot' (Lüdecke, 2021). Two final models were calculated for 60, 90, and 120 minutes, one for each PA parameter (sum of step and MET counts per time period) as dependent variables. Intraclass correlation coefficients (ICCs) of the null models indicated that 6% and 8% of variance for the main model (60 minutes) of step and MET counts respectively were due to between-person differences. Therefore, the influence of the hierarchical data structure was confirmed as the majority of the variance was explained by within-person differences. Hence, a multilevel approach was used. In contrast to the preregistration, the inclusion of level 3 (family) was not tested to avoid the overcomplication of the models. As all aspects of the JITAI were similar for children and adults as this was a family-based intervention, and children provided only a limited number of triggers, we chose to include all participants in the models while controlling for population. Assumptions were checked using the visualization of the ‘performance’ package (Lüdecke et al., 2021). As visual inspection pointed to no violation of the assumptions, no robust models were calculated. A hierarchical approach was used for the inclusion of the control variables and the model fit was assessed with the Akaike information criterion (AIC).

The dichotomous predictor condition (i.e. "not engaged" = 0, "engaged" = 1) was included at level 1 into the models and centered at the person-mean to estimate within-person effects (Hoffman & Stawski, 2009). Additionally, the control variables weekday or weekend (i.e. wewd, weekday = 0, weekend = 1), and time (i.e. time of the beginning of PA dummy coded as follows: morning (reference) = 00:00:00 to 11:59:59, afternoon = 12:00:00 to 16:59:59, and evening = 17:00:00 till 23:59:59) were included at level 1 to control for variability in the results over time (Liao et al., 2017). The person-mean of the respective condition as well as population (adult = 0, children = 1) were added as a between-person control variables at level 2 into the models. All control variables improved the model fit based on AIC and were therefore included in the final models. In contrast to the preregistration, the reason for the inactivity was not considered as a control variable because, in relation to the trigger, different time-windows were chosen for the "engaged" and "not engaged" condition which allow no direct comparison between conditions (see Figure 1). Random intercepts were used for all models and the level for significance was set a priori to $\alpha < 0.05$. The equation of the final models was:

Level 1 equation:

$$Y_{ij} = b_{0j} + b_{1j} * (condition)_{ij} + b_{2j} * (wewd)_{ij} + b_{3j} * (afternoon)_{ij} + b_{4j} * (evening)_{ij} + r_{ij}$$

Level 2 equation:

$$b_{0j} = \gamma_{00} + \gamma_{01} * (mean\ condition)_j + \gamma_{02} * (population)_j + u_{0j}$$

$$b_{1j} = \gamma_{10}$$

$$b_{2j} = \gamma_{20}$$

$$b_{3j} = \gamma_{30}$$

$$b_{4j} = \gamma_{40}$$

Results

Data availability and participant characteristics

Overall, 98 participants were included in the intervention group of the SMART*FAMILY*2.0 trial. The average number of days where the app was used for each participant was 17.39 out of 21, equating to 82.85% frequency of daily use (see elsewhere: Fiedler et al., 2022). Eighty-four of those participants received and answered at least one JITAI trigger during the 21-day intervention phase with a total of 1274 answered JITAI triggers and were included in this examination. Controlling for sufficient wear time (> 80%) in the 60/90/120 minutes following either the answering of the JITAI ("engaged" condition) or the sending of the JITAI ("not engaged" condition) led to 80/78/77 participants with 907/864/826 observations across both conditions respectively. As the JITAI could be triggered every 60-minutes, data of the 90- and 120-minutes timeframes were controlled for overlapping periods. This led to the final inclusion of 907/810/739 observations (80/80/79% adults) of 80/78/77 (59/60/61% adults) participants respectively. The following sections are referring to the 60-minute timeframe if not specified otherwise. Participant characteristics and PA separated by condition (n = 69 "engaged", n = 73 "not engaged"), population (child/adult), and sex (male/female) for transparency reasons (Schlund et al., 2021) are shown in Table 1. Due to the examination design and analysis protocol, individuals can be assigned to both groups. Strictly descriptive, the results showed that an average of 458.19 (SD = 813.25) steps were recorded in the hour after the trigger was answered ("engaged") in comparison to 353.55 (*SD* = 562.31) steps when the trigger was not answered ("not engaged").

Table 1

Descriptive data of all participants included in the analyses (N = 80, participants can but do not have to appear in both the "engaged" and the "not engaged" condition data). Displayed are the means(M) and standard deviations (SD) during three weeks for the parameters age, body mass index (BMI) steps, metabolic equivalent (MET) divided by condition ("engaged" or "not engaged"), population (children and adults), and sex (male and female).

condition	"engaged" (397 observations)				"not engaged" (510 observations)			
population	adult		child		adult		child	
sex	female (*n* = 20)	male (*n* = 21)	female (*n* = 17)	male (*n* = 11)	female (*n* = 22)	male (*n* = 23)	female (*n* = 16)	male (*n* = 12)
	M (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Age (years)	44.8 (5.70)	46.5 (4.98)	11.2 (2.81)	13.5 (3.39)	44.4 (5.29)	46.1 (5.02)	11.1 (2.95)	11.3 (4.11)
BMI (kg/m²)	24.0 (4.05)	26.6 (3.09)	17.5 (2.36)	19.3 (2.50)	23.7 (3.81)	26.9 (3.67)	17.2 (2.85)	17.9 (2.65)
steps (counts/hour)	627 (1020)	516 (1180)	391 (433)	952 (1430)	335 (356)	552 (1110)	832 (1400)	480 (714)
MET (counts/hour)	95.5 (34.1)	92.4 (36.9)	86.8 (26.2)	132 (94.4)	82.8 (14.9)	98.6 (55.6)	94.5 (34.9)	98.1 (45.3)

Figure 2 illustrates the average step count separated for both conditions within each person.

Figure 2

Step count in the 60 minutes following the trigger based on the condition (dots for each trigger, X and number for the mean for each condition) for each participant (1-80) for the "not engaged" condition (green) and the "engaged" condition (orange/red) which have been slightly jittered for better visualization. The black lines mark where adult data (n = 47) stops and children data (n = 33) begins.

397 of the 907 observations belong into the "engaged" condition, meaning that the participants received triggers due to inactivity and answered them within 60 minutes. Regarding the reason of inactivity, participants indicated that they did not have the time to be active (289 observations; 75%), did not want to be active (73 observations; 18%), or did not feel good enough to be active (28 observations; 7%). In seven cases, the participants indicated that they had been active but did not wear the sensor. Descriptive results show that the PA tends to be

higher after the trigger when participants did not have the time and did not want to be active in the previous minutes (see supplement Figure 1).

Effect of engaging with the just-in-time adaptive intervention on step count

Within-person effects (Level-1)

The results indicate a significantly higher step count in the "engaged" condition compared to the "not engaged" condition within-persons. In detail, if a person was triggered and answered the trigger within 60 minutes ("engaged"), he or she had 113.16 more steps recorded on average ($\beta = 0.08$, $p = .022$) in the hour following the answering compared to the 60 minutes after sending the trigger if the person did not respond within 60 minutes ("not engaged"). No other significant within-person effects were found. The results for 90/120 minutes found a significantly higher step count for "engaged" compared to "not engaged" within-persons. Furthermore, afternoon predicted significantly higher results compared to morning within-persons for 90 and 120 minutes and evening predicted significantly lower results compared to morning for 120 minutes.

Between-person effects (Level-2)

Results showed no significant effect between persons whose data was assigned to the "engaged" condition more often on average compared to persons whose data was assigned to the "not engaged" condition more often. However, significant differences between children and adults ($\beta = 0.08$, $p = .037$) were found which indicate that children had 138.10 more steps recorded in the hour throughout both conditions on average compared to adults. No significant influences of the between-person variables were found for 90 or 120 minutes. Overall, the ICC indicated that 3%/10%/7% of the variance in the models was due to between-person differences and 97%/90%/93% due to within-person variance for 60/90/120 minutes respectively.

Table 2

Multilevel model analysis for the influence of the intervention (i.e. just-in-time adaptive intervention) on step count (steps) in the 60/90/120 minutes following the trigger. Displayed are the within-person results of the person mean centered (mc) condition ("not engaged" (trigger has not been answered) = 0, "engaged" (trigger has been answered) =1), the within-person variable weekend/weekday (wewd, weekday = 0, weekend =1), and time (i.e. dummy coded morning (reference), afternoon, and evening). Additionally, the between-person results of the person mean (pm) condition ("not engaged" (trigger has not been answered) = 0, "engaged" (trigger has been answered) =1), and of population (adult = 0, children = 1) are displayed. All results are displayed using the raw estimates (count per timeframe), the standardized Beta (β), 95% confidence intervals (CI), and standardized (std.) 95% CI. Additionally, the within-person variance (σ^2), the between-person variance ($\tau_{00\ id}$), the intraclass correlation coefficient (ICC), the number of participants (N_{id}), the number of observations, and the marginal and conditional R^2 are displayed.

	steps 60					steps 90					steps 120				
Predictors	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*
(Intercept)	340.56	0.02	197.94 – 483.18	-0.06 – 0.10	<.001	494.43	0.03	246.20 – 742.66	-0.08 – 0.14	<.001	669.65	0.01	358.84 – 980.46	-0.09 – 0.11	<.001
condition_mc	113.16	0.08	16.54 – 209.78	0.01 – 0.14	.022	172.34	0.08	35.77 – 308.90	0.02 – 0.15	.013	181.52	0.07	8.64 – 354.41	0.00 – 0.14	.040
condition_pm	74.24	0.02	-201.84 – 350.32	-0.06 – 0.10	.598	241.98	0.05	-228.43 – 712.40	-0.05 – 0.15	.313	216.87	0.04	-337.54 – 771.28	-0.06 – 0.13	.443
population	138.10	0.08	8.56 – 267.64	0.00 – 0.16	.037	103.92	0.04	-122.05 – 329.90	-0.05 – 0.14	.367	162.77	0.06	-99.06 – 424.60	-0.03 – 0.15	.223
wewd	28.31	0.02	-84.13 – 140.75	-0.05 – 0.08	.622	98.16	0.04	-64.28 – 260.61	-0.03 – 0.11	.236	145.81	0.05	-56.09 – 347.71	-0.02 – 0.12	.157
afternoon	58.32	0.04	-43.33 – 159.96	-0.03 – 0.12	.261	151.47	0.08	7.16 – 295.79	0.00 – 0.15	.040	235.05	0.10	54.77 – 415.32	0.02 – 0.18	.011
evening	-87.02	-0.05	-208.06 – 34.02	-0.13 – 0.02	.159	-162.07	-0.07	-348.33 – 24.20	-0.14 – 0.01	.088	-246.70	-0.08	-492.25 – -1.15	-0.16 – -0.00	.049
Random Effects															
σ^2	450770.06					814737.88					1203517.79				
$\tau_{00\ id}$	13733.47					91955.52					97125.59				
ICC	0.03					0.10					0.07				
N_{id}	80					78					77				
Observations	907					810					739				
Marginal R^2 / Conditional R^2	0.019 / 0.048					0.027 / 0.126					0.035 / 0.107				

Effect of engaging with the just-in-time adaptive intervention on MET count

Within-person effects (Level-1)

Results indicate a significantly higher MET count in the "engaged" condition compared to the "not engaged" condition within-persons. In detail, if a person was triggered and answered the trigger within 60 minutes ("engaged"), he or she had 5.52 more MET counts recorded on average ($\beta = 0.08$, $p = .014$) in the hour following the answering compared to the 60 minutes after sending the trigger if the person did not respond within 60 minutes ("not engaged"). No other significant within-person effects were detected. The results for 90/120 minutes did not reveal any significant differences between "engaged" and "not engaged". Furthermore, evening predicted significantly lower results compared to morning for 90 and 120 minutes.

Between-person effects (Level-2)

Results showed no significant between-person effect for 60/90/120 minutes. The ICC indicated that 6%/14%/7% of the variance in the models was due to between-person differences and 94%/86%/93% due to within-person variance for 60/90/120 minutes respectively.

Table 3

Multilevel model analysis for the influence of the intervention (i.e. just-in-time adaptive intervention) on metabolic equivalents (MET) in the 60/90/120 minutes after the trigger. Displayed are the within-person results of the person mean-centered (mc) variable condition ("not engaged" (trigger has not been answered) = 0, "engaged" (trigger has been answered) =1), the within-person variable weekend/weekday (wewd, weekday = 0, weekend =1), and time (i.e. dummy coded morning (reference), afternoon, and evening). Additionally, the between-person results of the person mean (pm) condition ("not engaged" (trigger has not been answered) = 0, "engaged" (trigger has been answered) =1), and of population (adult = 0, children = 1) are displayed. All results are displayed using the raw estimates (count per timeframe), the standardized Beta (β), 95% confidence intervals (CI), and standardized (std.) 95% CI. Additionally, the within-person variance (σ^2), the between-person variance ($\tau_{00\ id}$), the intraclass correlation coefficient (ICC), the number of participants (N_{id}), the number of observations, and the marginal and conditional R^2 are displayed.

	MET 60					MET 90					MET 120				
Predictors	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*	*Estimates*	*std. Beta*	*95% CI*	*standardized 95% CI*	*p*
(Intercept)	86.99	0.03	79.84 – 94.13	-0.06 – 0.12	<.001	131.74	0.04	120.12 – 143.36	-0.08 – 0.16	<.001	173.72	0.01	159.35 – 188.09	-0.09 – 0.11	<.001
condition_mc	5.52	0.08	1.12 – 9.92	0.02 – 0.14	.014	5.26	0.06	-0.65 – 11.18	-0.01 – 0.12	.081	7.36	0.06	-0.79 – 15.52	-0.01 – 0.13	.077
condition_pm	3.36	0.02	-10.84 – 17.57	-0.07 – 0.11	.643	7.31	0.04	-14.88 – 29.50	-0.07 – 0.14	.519	11.10	0.04	-14.45 – 36.65	-0.05 – 0.13	.394
population	4.66	0.06	-1.93 – 11.24	-0.02 – 0.14	.166	1.65	0.02	-9.08 – 12.37	-0.09 – 0.12	.764	4.45	0.03	-7.60 – 16.50	-0.06 – 0.12	.469
wewd	-0.58	-0.01	-5.75 – 4.58	-0.07 – 0.06	.825	1.98	0.02	-5.10 – 9.07	-0.05 – 0.09	.583	2.52	0.02	-6.98 – 12.02	-0.05 – 0.09	.603
afternoon	1.77	0.03	-2.90 – 6.45	-0.05 – 0.10	.457	4.04	0.05	-2.25 – 10.33	-0.03 – 0.12	.208	7.03	0.06	-1.45 – 15.52	-0.01 – 0.14	.104
evening	-4.87	-0.06	-10.45 – 0.71	-0.14 – 0.01	.087	-11.26	-0.10	-19.39 – -3.13	-0.18 – -0.03	.007	-16.62	-0.11	-28.17 – -5.07	-0.19 – -0.03	.005
Random Effects															
σ^2	934.63					1527.87					2677.15				
$\tau_{00\ id}$	58.03					249.11					190.06				
ICC	0.06					0.14					0.07				
N_{id}	80					78					77				
Observations	907					810					739				
Marginal R^2 / Conditional R^2	0.016 / 0.074					0.022 / 0.159					0.030 / 0.094				

Discussion

The present examination showed that engagement with a JITAI triggered by a period of physical inactivity is associated with enhanced device-based measured PA in the subsequent hour. Given that evidence on the momentary effect of engagement with JITAI prompts on free-living PA is yet scarce, an important feature of this examination was the comparison of the steps and MET counts in the 60-minute timeframes after the inactivity trigger was answered ("engaged") with the 60-minute timeframes when the inactivity trigger was not responded to ("not engaged"). Overall, results showed that engagement with the basic JITAI implemented in the SMART*FAMILY*2.0 app produced promising results concerning PA enhancement in the subsequent hour after the trigger was answered which needs to be confirmed by future studies especially under the consideration of causality.

Results of previous predominantly feasibility studies with small sample sizes indicated the potential of JITAIs to interrupt phases of physical inactivity in individuals with overweight and obesity (Bond et al., 2014; Finkelstein et al., 2015) and individuals with diabetes (Pellegrini et al., 2015). In the above-mentioned studies, the influences of JITAI on accumulated PA outcomes like steps and categories of PA was investigated either longitudinally on a daily level (Bond et al., 2014), by the comparison of pre- post-intervention (Pellegrini et al., 2015), or in a randomized controlled crossover design (Finkelstein et al., 2015). The current results enhance the understanding of the association of the engagement with JITAI triggers for subsequent PA behavior directly after the trigger for two different PA measures in a non-clinical sample. Bond et al. (2014) found that a JITAI which was triggered after various periods of inactivity reduced daily values of physical inactivity and enhanced light and moderate PA during the seven day intervention period if compared to a baseline week without a JITAI. Our examination adds that step and MET counts in the 60 minutes directly after the engagement with the trigger are enhanced compared to if the trigger assumedly has not been noticed or has been ignored by the participant. Furthermore, the exploration of 90 and 120 minutes after the trigger indicated a time persistent effect of engagement with the JITAI on step count while the effect vanished for MET count. This points to potential differences for measures related (i.e. MET) and unrelated (i.e. steps) to the intensity of the movement (Silfee et al., 2018).

The time variables referring to morning, afternoon, and evening and to weekend vs. weekday had no significant influence on the outcomes for the main model. However, step count was higher in the afternoon for the model using 90 minutes and lower in the evening for 120 minutes while MET count significantly decreased in the evening for both 90- and 120-minute models. This points to dynamic associations and temporal influences of the time in the day to PA measures which should be explored in greater detail by future studies to improve the implementation of JITAI-specific features referring to decision points and rules. An important aspect could be to adjust the time frames of the triggers if there will be less PA late in the evening but more opportunities for PA directly after work/school in the afternoon.

Further interesting descriptive insights are provided in table 1. Here, the outcome for the two conditions appears to depend on the combination of population and sex. For example, female adult step count is higher in the engaged when contrasted against the not engaged condition while female child data suggests reverse results. As this is beyond the scope of the manuscript, the analysis of the age and sex-specific peculiarities of participants would be important to address in future research.

The current examination also provides some exploratory and preliminary indications on the question, if the reason for previous inactivity is associated to the subsequent activity. Here, descriptive results indicate higher variance in step count for the hour following the answering of the trigger if participants stated that they did not have time compared to if they did not want to be active (supplement Figure 1). Furthermore, if participants stated that they were feeling unwell, PA remained low in the following hour. This supports the assumption that including user-input into the decision-making process is a valuable source of information in a JITAI (Wunsch et al., 2022). The credibility and usefulness of the intervention can benefit by accounting for participants' experiences which enhances user engagement and effectiveness during interventions (Vandelanotte et al., 2016). One example could be to suppress triggers if the participant feels unwell as PA after such triggers remained low in this exploratory analysis. This would be beneficial for the aim of increasing the competence of the participants by the behavior change technique to "teach how to use prompts/ and cues" (Michie et al., 2011) as only the triggers in true opportune moments for behavior change would be received by the participants. Therefore, future studies should further investigate the reason for inactivity and consider adding it as user-input included in a decision rule at a decision point for the JITAI. Additionally, core affect might be an important aspect as it was related to daily PA in a previous examination within the same study (Fiedler et al., 2022). Here, valence and energetic arousal are known to be positively associated with PA while calmness is negatively associated with PA in adults (Forster et al., 2021) and children (Koch et al., 2018). Further contextual factors of inactivity (Giurgiu et al., 2020) like the location, weather, availability, and personal preferences of the participant should also be considered to enhance the identification of true opportune moments in future studies.

Strengths and limitations

The primary strength of this examination is that it was conducted in a real-time intervention setting and involved 80 children, and adults, two different device-based measured

PA outcomes, an extended measurement period of 21 days, and that the design and reporting are guided by a comprehensive JITAI framework (Wunsch et al., 2022). Additionally, the use of multilevel analysis allows for the inclusion of all triggers independently while controlling for the hierarchical structure of the data. This allows for a robust estimation of the effect of engaging with the JITAI.

However, certain limitations need to be considered when interpreting the results of the current investigation. First, included adults and children were already quite active with around 8000 steps and more than 50 minutes of moderate to vigorous PA per day on average while the app was used on 88% of the days (see Fiedler et al., 2022). This limited the number of triggers to be analyzed, especially for children. Another aspect was, that the participants had to use provided smartphones instead of their own which can be burdensome and might explain why over 50% of triggers were not answered within 60 minutes. Here, previous research showed that participants who used their own smartphone showed no difference in missed events compared to participants who used an additional smartphone (Ziesemer et al., 2020). One alternative approach for this problem could be to use wearables which can integrate the accelerometer and a small display to respond to JITAIs at the potential cost of the accuracy of the measurement (Feehan et al., 2018). A further limitation was the lack of theoretical underpinning of the message tone regarding the JITAI trigger which has been recommended by Pope and colleagues (Pope et al., 2018). This could be achieved by following the recommendations of the physical activity messaging framework (Williamson et al., 2021). However, the JITAI itself was based on a behavior change technique (Michie et al., 2011) which supports the psychological need for competence in the self-determination theory (Ryan & Deci, 2000). The most important limitation is, that the "not engaged" condition cannot be interpreted as an independent control condition with no possible influence by the intervention. Furthermore, participants assigned to the "not engaged" condition might have noticed the trigger but simply did not interact with the app and therefore did not create a timestamp. To answer the question regarding the effectiveness of the JITAI and not the association of the engagement with the JITAI with subsequent PA, micro-randomized trials should be considered to provide a better-controlled comparison and provide insights into causality in the future (Conroy et al., 2020). Finally, it needs to be noted that this examination was a secondary data analysis of a larger study aimed to enhance PA and healthy eating (Wunsch et al., 2020) where the JITAI is only one part of the intervention procedure, which was examined in separation. However, by focusing on the momentary effects, the influences of other interventional aspects like the influence of providing information, and goal setting are assumed to be limited. Data of the same intervention period but different outcomes, namely core affect and sleep quality values per day, has been used in a previous publication (Fiedler et al., 2022).

Conclusion

The examination expands previous findings on JITAIs by focusing on the engagement with the JITAI and by considering the temporal associations between the trigger and the outcome in a multilevel approach in children and adults. The results underline the importance of participants' engagement with JITAI triggers to interrupt inactive phases. Here, factors like time of the day and the reason for the inactivity are possibly important influences on PA measures. Future studies should further refine the understanding of opportune moment identification by involving participants in JITAI design and building on existing findings from ecological momentary assessment research (e.g. Giurgiu et al., 2020). These important tailoring variables like the core affective state of the participants and contextual factors like availability and weather should then be used to enhance the adaptation to participants' needs and therefore the engagement and effectiveness of JITAIs.

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