Sedentary work in desk-dominated environments

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Design, development, production, and evaluation of a workplace sedentary behavior intervention

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DISSERTATION

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CHAPTER 1

General introduction

Technological developments in western countries lead to an increase of office work encompassing on average around 60% sedentary behavior (Prince, Elliott, Scott, Visintini, & Reed, 2019). For example, in the US, the prevalence of sedentary occupations has statically increased from 15% office jobs in 1969 to over 20% in 2008 (Church et al., 2011). The high prevalence of office work in the last decade is remaining relatively stable (Loyen et al., 2018). Yet, evidence has accumulated that sedentary behavior, independent from moderate-to-vigorous physical activity (MVPA), harmfully affects short- and long-term aspects of health and well-being. Risks for physical complains such as cardiovascular disease (Carter, Hartman, Holder, Thijssen, & Hopkins, 2017) as well as diabetes type 2 (Patterson et al., 2018), and possibly mental health problems (Magnon, Vallet, & Auxiette, 2018) are elevated. Office workers' mortality risks were found to be 35% higher than that of those employees having jobs requiring more physical work, such as walking and lifting (Chau et al., 2015). Nevertheless, there is a "physical activity paradox" which suggests, among others, that the health effects of the physical activity being carried out at work differ from the effects of physical activity being performed during leisure-time (Holtermann, Krause, Van Der Beek, & Straker, 2018). Replacing sedentary activities with physical activities therefore needs to be carefully thought through and the benefits cannot only be attributed to the intensity of physical behaviors (i.e. sedentary behaviors and physical activity behaviors). Hence when replacing sedentary behavior, it is not merely replacing sitting with a behavior with higher energy expenditure but it also depends on the context in which it is performed, the pattern (e.g. standing and sitting are negative if static and prolonged), and the way it is performed (e.g. awkward postures, repetitive or asymmetric movements).

Initially, sedentary behavior was considered as equivalent to physical inactivity, which refers to a non-attainment of the WHO's physical activity recommendation to accumulate 150 minutes of MVPA per week (World Health Organization, 2010). Although sedentary behavior might correlate with physical inactivity, a clear distinction between those concepts is crucial for the understanding of sedentary behavior (Panahi & Tremblay, 2018). For example, standing and light physical activity neither contribute to meeting the

WHO's recommendations nor would they be described as sedentary, considering the Latin etymology (sedere = to sit). Indeed, sedentary behavior has recently been defined as any low energy-expending behavior (below 1.5 metabolic equivalents, METs) that is performed in a sitting, reclining or lying position, excluding sleep (Tremblay, Aubert, et al., 2017). METs refer to the energy costs that are involved when performing specific activities. When sitting at rest, the amount of oxygen being consumed is equal to one MET (Jette, Sidney, & Blümchen, 1990), and physical activity is categorized in light intensity (1.5 - 3.0 METs), moderate intensity (3.0 – 6.0 METs), and vigorous intensity (> 6.0 METs) physical activity (American College of Sports Medicine, 2013). One of the proposed explanations accounting for the independent association of sedentary behavior with cardiometabolic risk suggests that static posture of the lower limbs during prolonged sitting downregulates the endothelial functions by reducing blood flow, which, eventually, increases blood pressure (Carter et al., 2017). Therefore, while the physical activity guidelines are not necessarily met, each interruption from prolonged, uninterrupted sitting, whether combined with MVPA, light physical activity, or standing, can contribute to a health benefit (Duvivier et al., 2017). Hence, sedentary behavior is distinct from physical inactivity, and neither should those concepts be amalgamated in research nor health promotion.

Not only definitions but also ways of operationalization and recommendations concerning sedentary behavior diverge. Sedentary behavior measured in the total time of a day seems to be only detrimental if more than 10 hours of sitting time are accumulated (Bankoski et al., 2011). Additionally, there is advice against long and uninterrupted sitting bouts (Healy et al., 2008) or suggestions that all physical behaviors during waking hours should be composed healthily, e.g. sitting should constitute maximally around 42-47% of the day being combined with at least 10-15% MVPA (Chastin, Palarea-Albaladejo, Dontje, & Skelton, 2015). Similarly, scientists resoundingly emphasize that the attainment of the suggested amount of MVPA cannot compensate for the detrimental effects of sedentary behavior (Bankoski et al., 2011; Ekelund et al., 2016; Hamilton, Healy, Dunstan, Zderic, & Owen, 2008; Pandey, Salahuddin, Garg, & et al., 2016; Thorp, Owen, Neuhaus, & Dunstan, 2011). For that reason, sedentary behavior interventions that effectively reduce overall as well as prolonged sedentary behavior in office workers are strongly needed.

Existing interventions

Sedentary behavior interventions that showed long-term effects for reducing sedentary behavior frequently incorporated a compendium of behavior change methods (Gardner, Smith, Lorencatto, Hamer, & Biddle, 2016; Stephenson, McDonough, Murphy, Nugent, & Mair, 2017). The practical components of the interventions being effective often included a personal coach and/or environmental adaptions, such as the installation of standing or treadmill desks (Coffeng et al., 2012; Kwak et al., 2007; McEachan, Lawton, Jackson, Conner, & Lunt, 2008). Similarly, recent reviews on the effectiveness of sedentary behavior interventions revealed that interventions involving environmental restructuring showed promising effects (Hutcheson, Piazza, & Knowlden, 2018), while there is mixed evidence concerning interventions focusing on persuasion (i.e., changing the structure of individuals' beliefs) only (Commissaris et al., 2016; Wang, Wu, Lange, Fadhil, & Reiterer, 2018). Although self-monitoring, prompts/reminders, and education sessions are methods that, when being combined, show promising results when it comes to workplace sitting, the evidence of persuasion-only interventions is still lacking (Compernolle et al., 2019; Wang et al., 2018).

Since environmental restructuring and personal coaches involve relatively high financial and time-based expenditures, cost-efficient alternatives are warranted. With recent technological advances, interactive computer and smartphone applications pave the way to remote yet tailored advice (Broekhuizen, Kroeze, van Poppel, Oenema, & Brug, 2012; Kelders, Kok, Ossebaard, & Van Gemert-Pijnen, 2012; Schoeppe et al., 2016). In addition, objective physical behavior measurement tools nowadays frequently include hardware and software that allow for a wireless transfer (via Bluetooth and internet) of physical behavior data, which is essential for tailored advice (Atkin et al., 2012). Therefore, a remote, yet personalized sedentary behavior intervention that provides tailored and personalized advice could be a solution towards an effective intervention at reduced costs.

Sedentary behavior measurement tools

Valid and reliable measurement tools are crucial for sedentary behavior interventions given that they create awareness through monitoring and enable tailored advice as well as the evaluation of intervention effects (Atkin et al., 2012; Gardner et al., 2016; Hutchinson, Breckon, & Johnston, 2009). Self-reporting of sedentary behavior burdens participants and shows lower psychometric properties compared to objective measurement tools such as accelerometers (Atkin et al., 2012). Accelerometers that are applied can measure dynamic as well as static accelerations, e.g. ActivPAL (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011), Actigraph (Júdice, Teixeira, Silva, & Sardinha, 2019). Generally, accelerometers mostly encompass three axes measuring horizontal, vertical, and diagonal accelerations that can be read and integrated providing information about postures and activity types (Plasqui, 2017). Although wrist-worn accelerometers might be able to distinguish physical activity from physical inactivity and ease monitoring and wearability, they cannot accurately distinguish sitting from standing (D. Y. Kim, Jung, Park, & Joo, 2014). As abovementioned, when investigating sedentary behavior, standing and light physical activity are as important as MVPA. Therefore, accelerometers that are worn at the upper thigh and that can distinguish between postures should be employed. Valid tools that are already utilized in research are the inclinometer function of the Actigraph or the ActivPal (Plasqui, Bonomi, & Westerterp, 2013). However, these tools are cost-intensive, require profound knowledge about the reduction and the cleaning of the raw data, and do not provide opportunities for data transfer while being in the tenure of participants (Atkin et al., 2012). VitaBit Software (VitaBit Software International B.V., Eindhoven, The Netherlands) developed a device at low-cost that aims to distinguish between postures while allowing for almost real-time data transfer between device users and researchers, analysts or coaches. It was therefore considered as a potential measurement tool for a workplace sedentary behavior intervention.

Intervention Mapping

Behavior change interventions involve a compendium of applications that are designed to change the specified behavior and underlying patterns. If interventions are found to be effective in altering the behavior at hand and considered as best practice, they have the potential to be implemented in practice to promote health in large parts of the population. Despite numerous successful health behavior interventions, there are also examples of interventions that are implemented but that were not found to be effective. Reasons are manifold but they can comprise among others incomplete implementation in practice, poor adoption by the target group, or incomplete use of theories and evidence due to for example time-constraints. Additionally, health behaviors are often very complex and influenced by numerous environmental and psychosocial factors on different ecological levels (e.g. interpersonal, societal, organizational level). To increase the likelihood of an intervention to be effective, frameworks are available that guide systematic intervention development by helping program planners to ask and answer the right questions at the right time during intervention development (Buunk & Van Vugt, 2013; Ruiter, Massar, van Vugt, & Kok, 2013). Example questions are: "How to select theories?", "How to translate theories into behavior change methods?", or "What is necessary to implement practical applications into this setting?". These frameworks often include guidance on how to analyze the risk behaviors and underlying structures, such as environmental factors, psychosocial determinants, and sub-behaviors being involved. Additionally, most of the frameworks provide guidance on planning implementation and evaluation of the intervention. During the entire process, the correct application of evidence from theory, literature, and empiricism facilitates the process and increases the likelihood of the intervention to be effective (Ruiter & Crutzen, 2020). A framework for systematic intervention development helps to keep an overview of all the tasks that need to be performed for comprehensive intervention design.

There are many existing frameworks for intervention development. Yet, many of these are not comprehensive, in a way that they neglect the complexity of behaviors and behavioral change. For example, some frameworks focus on the design of the practical applications only, while they do not involve a structured analysis of the problem behavior and the important determinants, or different ecological levels that are involved with the behavior (Dolan, Hallsworth, Halpern, King, & Vlaev, 2010; Michie, van Stralen, & West, 2011). Other frameworks neglect that behaviors often comprise sub-behaviors which themselves need to be targeted by changing specific underlying beliefs. For example, while focusing on the main component of an intervention, such as a gamified mobile phone application to stop smoking, developers might forget that the behavior also involves downloading the application, which probably requires the expectation, that downloading this app will yield positive results. Therefore, a framework may help intervention planners to find solutions that are both comprehensive and well researched (Ruiter & Crutzen, 2020).

In a recent overview which reviewed approaches for intervention development, the authors identified 18 key actions that are recommended to be considered during intervention development. Thereby, the Intervention Mapping (IM) protocol has been found to be the most comprehensive approach that includes the highest proportion of these key actions (O'Cathain et al., 2019). The Intervention Mapping (IM) protocol is a framework for the preparation, the development, the implementation, and the evaluation of behavior change interventions. It describes six iterative steps: (1) conducting a needs assessment; (2) specifying program outcomes and objectives; (3) selecting behavior change methods and practical applications; (4) planning program production; (5) planning program implementation; and (6) planning program evaluation (Bartholomew Eldredge et al., 2016; Crutzen & Peters, 2018). All steps are thoroughly informed by systematically going through the Core Processes of using evidence from theory, literature, and, if necessary, supplementary empirical research (Ruiter & Crutzen, 2020). Additionally, different ecological levels potentially influencing the performance of the target behaviors, such as the interpersonal level (i.e., colleagues and supervisors) or the organizational level (i.e., companies), are considered. The IM protocol further suggests the establishment of a planning group comprising stakeholders that could contribute to the development, implementation, and/or the evaluation of the intervention (Bartholomew Eldredge et al., 2016).

In the first IM step, the health problem at hand is investigated. Thereby, the consequences of risky behaviors on health and quality of life as well as personal and external factors causing the risk behaviors are identified. In the second IM step, program outcomes are formulated. More specifically, behavioral outcomes, such as “interrupt sitting every 30 minutes”, are formulated and sub-divided into performance objectives or sub-behaviors (e.g., set a challenging coal, monitor personal behavior). Every performance objective is combined with a variety of psychosocial determinants, such as self-efficacy and attitude. In the IM protocol, the focus is on the identification of relevant and changeable determinants. Relevance refers to the strength of the determinant’s association with the outcome behavior and changeability refers to the likelihood that an intervention component can modify the determinant (Peters & Crutzen, 2018). Furthermore, change objectives (e.g., specific skills, beliefs) combine determinants with performance objectives: they provide information on what about a determinant needs to change to, eventually, target a performance objective. For example, “demonstrate the skills to set good goals” (change objective), being part of “self-efficacy” (determinant), should be promoted in order to help participants “set good goals” (performance objective), which, eventually, helps to “interrupt sitting” (behavioral outcome). In the third IM step, behavior change methods (e.g. self-monitoring of behavior) are chosen by analyzing their potential to change the related determinant. These constitute the basis for designing practical applications (e.g., “participants monitor their sedentary behavior via a mobile phone application”). In this regard, the behavior change method is matched to the change objectives while taking into account the parameters of use (e.g. “Monitoring must be of a specific behavior and data must be interpreted and used”). In the fourth IM step, program messages and intervention components are designed based on the practical applications. Program components are pilot-tested, refined, and produced. In the fifth IM step, an adoption, implementation and sustainability plan is created by re-applying IM-steps 1 to 4. In the sixth IM step, the assessment of the effects of the intervention and underlying mechanisms of these effects (process evaluation) are planned. Indicators and measures are collected, and the design as well as the procedure of the evaluation studies are anticipated (Bartholomew Eldredge et al., 2016).

Determinants of sedentary behavior

As abovementioned, several determinants and more specifically change objectives can influence the likelihood of a behavior being performed. Examples of change objectives regarding sedentary behavior are: “Recognize advantages of reducing sedentary behavior” *(attitude)*, “Express confidence to set adequate goals” *(self-efficacy),* and “Indicate that they are supported by colleagues” *(Perceived social support)* (De Cocker, De Bourdeaudhuij, Cardon, & Vandelanotte, 2015). Most of the change objectives that are relevant for sedentary behavior can be addressed via behavior change methods.

One specific aspect of the attitude towards interrupting sitting, which is frequently mentioned in the literature, is perceived tiredness (Chastin, Buck, et al., 2015). This is one of the rare aspects that needs to be changed through alteration of another health behavior, which would require another IM process: promoting sleep hygiene. A method to assess whether there is a relationship between tiredness and sedentary behavior is to investigate associations of sleep duration (a proxy for tiredness) with the next day’s sedentary behavior. Indeed, among a female population, longer sleep was associated with less time spent in sedentary behavior during the following day (Gabriel et al., 2017). However, it needs to be mentioned that the ratio between sleep and sedentary behavior is codependent: More sleep leads to less time awake, which consequently leads to less time that can be spent sitting, standing or moving (Chastin, Palarea-Albaladejo, et al., 2015). Therefore, it is important to analyze the influence of long and short sleep on compositions of all physical behaviors using a compositional data approach. This could reveal first insights into whether sleep duration (as proxy for perceived tiredness) affects the healthiness of physical behavior compositions.

Objectives of this dissertation

The main objective of this dissertation was to develop a sedentary behavior intervention being based on a new sensor (VitaBit). Therefore, we applied the IM protocol to systematically design and evaluate an intervention aiming at the reduction of prolonged and total sitting among desk workers.

Outline of this dissertation

As prerequisite to the intervention development, a validation study was performed comparing the output of the novel VitaBit sedentary behavior sensor with direct observation and with inclinometer output of the Actigraph GT3X+ in both a laboratory and a free-living condition (**Chapter 2**). Since the VitaBit showed acceptable validity values, this brought us to the design of the intervention. **Chapter 3** covers the six iterative steps of the IM protocol to describe the development of the program design, a pre- and a pilot-test, the implementation planning, and the organization of the evaluation. In the process, evidence from literature and theory was gathered. If relevant information for the development of the sedentary behavior intervention was missing, knowledge was utilized through empirical studies. For IM steps 3 and 4 (program design and planning of program production), information about the acceptability and effectiveness of program components was missing. Therefore, two qualitative studies were performed: a pre-test to test the acceptability of first program components, and a pilot study to test the effectiveness of the entire program among a small cohort of 11 participants. The intervention encompassed two parts: the toolkit of the VitaBit sensor (monitoring app and computer dashboard) and the motivational support “UPcomplish”.

For IM step 1 *(needs assessment)*, information about the sub-determinant “perceived tiredness” was missing. In **Chapter 4,** we tested a potential methodology for investigating the bi-directional association between sleep duration and sedentary behavior. A compositional data approach was applied to transform the physical behavior compositions into variables that can be inserted in regression models. We analyzed the associations of sleep duration on the following day's physical behavior proportions, and the associations of physical behavior proportions with the sleep durations of the succeeding night, both nested within individuals. For this study, we used data from the Focus on Strength randomized controlled trial (FoS). In the FoS, Dutch adolescents (11-15 years) were provided with strength exercises and motivational sessions to evaluate the effects on physical activity levels and, eventually, body composition over a 1-year period. The participating adolescents wore an Actigraph GT3X and filled out sleep diaries both at the beginning of the RCT and at 1-year follow-up. For this chapter, we used data of 231 adolescents that provided enough sleep diaries and valid accelerometer data (Ten Hoor et al., 2016; Ten Hoor et al., 2018).

For IM step 2 *(program outcomes and objectives)*, evidence about recommended sedentary behavior patterns in terms of health was contradictory. Researchers seem to agree that sedentary behavior should be regularly interrupted, but there was no consensus about the operationalization of sedentary patterns. Therefore, we developed an algorithm (SPORT) that is able to reduce complex information on sequential physical activity patterns in such a way that it can be inserted in linear regressions models or used for real-time feedback in interventions. We validated the algorithm in a cohort of adolescents from the FoS RCT using a cross-sectional study design and compared the predictive power with the traditional compositional data approach (**Chapter 5**).

After the development and the refinement of the measurement and monitoring toolkit VitaBit and the motivational and tailored support by a personal coach, UPcomplish, we aimed for an evaluation of their effectiveness. In **Chapter 6**, we applied a stepped-wedge design to evaluate the intervention effects. Thereby, the intervention was implemented among 5 groups of office workers each starting with time-lags of 7 weeks. Between- and within subjects, phases including both UPcomplish and VitaBit were compared with VitaBit only phases. Putative mechanisms of intervention effects are specified in the process evaluation in **Chapter 7,** which provides more detailed information about the effectiveness of the intervention and the basis for further adaptation of the intervention.

CHAPTER 2

Validation of the VitaBit sit-stand tracker: Detecting sitting, standing, and activity patterns

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Abstract

Objectives. Sedentary behavior (SB) has detrimental consequences and cannot be compensated for through moderate-to-vigorous physical activity (PA). In order to understand and mitigate SB, tools for measuring and monitoring SB are essential. While current direct-to-customer wearables focus on PA, the VitaBit validated in this study was developed to focus on SB.

Methods. It was tested in a laboratory and in a free-living condition, comparing it to direct observation and to a current best-practice device, the ActiGraph, on a minute-by-minute basis.

Results. In the laboratory, the VitaBit yielded specificity and negative predictive rates (NPR) of above 91.2% for sitting and standing, while sensitivity and precision ranged from 74.6% to 85.7%. For walking, all performance values exceeded 97.3%. In the free-living condition, the device revealed performance of over 72.6% for sitting with the ActiGraph as criterion. While sensitivity and precision for standing and walking ranged from 48.2% to 68.7%, specificity and NPR exceeded 83.9%.

Conclusions. According to the laboratory findings, high performance for sitting, standing, and walking makes the VitaBit eligible for SB monitoring. As the results are not transferrable to daily life activities, a direct observation study in a free-living setting is recommended.

Introduction

Consequences of uninterrupted sitting entail high risks of developing metabolic and cardiovascular diseases, certain types of cancers, and all-cause mortality (Biswas et al., 2015; Wilmot et al., 2012). Additionally, first evidence suggests that negative psychological impact caused by sedentary behavior (SB) should not be neglected (Hamer & Stamatakis, 2014; Hendriksen, Bernaards, Steijn, & Hildebrandt, 2016). The psychological and physical consequences of SB were found to occur independently of other health-related behaviors, such as leisure time moderate-to-vigorous physical activity (PA) (Hamilton et al., 2008; Thorp et al., 2011). Although high levels of PA, i.e., more than 5 h of jogging per week, might mitigate the risk of overall sitting time, it was found that it does not eliminate the risks associated with TV watching time of more than 5 h (Ekelund et al., 2016). Therefore, it is likely that PA cannot mitigate the risks of specifically uninterrupted overall sitting time. Given the rising estimated prevalence of SB, increased attention is drawn to interventions that aim to overcome detrimental sitting and subsequent increased risk (Bauman et al., 2011; Gardner et al., 2016).

When developing and evaluating these SB interventions, objective measurement and monitoring tools for SB and its antagonist behaviors (standing or walking) are indispensable. In order to create awareness for a putative behavioral change, those measurements need to display deviations of the users' actual sit–stand–walk patterns from the recommendations (Gardner et al., 2016; Hutchinson et al., 2009). Furthermore, they are needed to refine recommendations for activity patterns (e.g., "It is recommended to interrupt sitting at least once per hour by either 10 min standing or 2 min walking") and to develop and improve behavioral change programs (Hamilton et al., 2008). Yet, a valid direct-to-consumer SB monitor is currently not available (Atkin et al., 2012).

Current objective best-practice trackers applied in SB research with high accuracy are tri-axial accelerometers like the ActiGraph (GT3X+, ActiGraph, Pensacola, FL, USA) or posture monitors like the ActivPal (PAL Technologies Ltd., Glasgow, UK) (Atkin et al., 2012). However, these still come with high-cost soft- and hardware or require profound knowledge on data analysis (Berger et al., 2008). Current direct-to-consumer monitors (e.g., Flex 2, Fitbit) focus more on PA than on posture detection such as sitting and standing (Dominick, Winfree, Pohlig, & Papas, 2016; Gomersall et al., 2016; Imboden, Nelson, Kaminsky, & Montoye, 2017). The VitaBit device used for the current study distinguishes sitting, standing, and walking and offers, among others, a monitoring tool for the end user. It further provides behavioral change specialists with a tool to interact (e.g., e-mails or push-messages) and individually adapt their health suggestions (e.g., based on activity data, compliance, or goal-setting behavior) to the end-user. The standard list price on the website is €99.95 (excluding VAT), including the monitor and one-year usage of apps, web portal, and data analysis/export functionality, while pricing for over 10 monitors is upon request.

In this paper, we examine the validity of the new VitaBit (VitaBit Software International B.V., Eindhoven, The Netherlands) accelerometer in a laboratory and free-living setting with direct observation and ActiGraph output as criterion measurements, respectively. Regarding device performance measurements, we were specifically interested in the evaluation of binary classifiers, more detailed in sensitivity, specificity, positive (PPR, also referred to as precision) and negative (NPR) predictive rate.

Methods

Sample

Fourteen participants (11 females, three males) volunteered for the laboratory study (nine females, two males) and/or the free-living study (six females, one male) and its sub-study (six females, three males). Volunteers were required to have an Android or iOS smartphone and to be willing to download the VitaBit smartphone application (https://www.vitabit.software/en-GB/), aged between 18 and 50 years, and fluent in English or German. People with any condition preventing them from performing the exercise protocols (Medical Screening Questionnaire in Appendix A) were excluded from the study. Prior to participation, informed consent was obtained. Ethical approval had been obtained by the Ethics Review Committee Psychology and Neuroscience, Maastricht University, the Netherlands (ECP-04-09-12). The cleaned datasets and the code for analyses in R can be found in DataverseNL (http://hdl.handle.net/10411/H5PZCT).

VitaBit as a measurement tool

The VitaBit device is a small, cuboid accelerometer (3.9 × 1.4 × 0.85 cm, 4.8 g) with long battery life (>30 days with auto-synchronization) that is worn at the thigh. It can be placed in the front pocket of the pants or be attached to tights or pocket-less trousers and skirts, as a magnetic clip helps to fix it to a garment layer. The VitaBit hardware includes a Micro-Electro-Mechanical Systems (MEMS) motion sensor, which is a tri-axial linear accelerometer and a wireless microcontroller targeting, among others, Bluetooth applications. The sensor is capable of detecting accelerations with an amplitude range of −16 to +16 g and 6D/4D orientations with a sampling rate of 33 Hz and an output data rate of 30 s. Via a proprietary algorithm, the processor samples pedometer data to calculate whether the output for a 30-second period is categorized as walking; if the output is not walking, the algorithm differentiates between sitting and standing. Thereby, the VitaBit regulatory recalibrates, eliminating the necessity of a determined device orientation in space, which makes it easy to deploy on a daily basis. The device stores activity and sitting data for at least 30 days, which can be synchronized with a connected smartphone application (requiring iOS 7.1/Android 4.3 or higher) via a Bluetooth Low Energy connection. After synchronization of the device with the smartphone app, the app sends the data via a wireless Internet connection to a back-end server. The data are processed nearly in real time and securely stored in a time series database, before they are used by a web-based analytics portal (https://www.vitabit.software/en-GB/).

Protocol

This observational study consisted of two parts, a laboratory part in which we examined the validity of the SB tracker in a controlled and directly observed laboratory setting, and a free-living part, in which the VitaBit was validated against one of the current best-practice trackers, the ActiGraph (Atkin et al., 2012). During the three parts of the lab-controlled study, participants wore the VitaBit in their pockets or attached the monitor close to their pocket using a magnet in case no or only loose pockets were available. Pre-inspection of the data revealed no difference between the two ways of attachment. They were instructed to walk, sit down, and stand up in different predetermined paces while being observed by the experimenter. Within the free-living part, a "sub-study" was conducted to validate the ActiGraph's eligibility as a measurement criterion. A sub-sample of subjects wore the ActiGraph on their thigh using an elastic band during the laboratory conditions (Figure 1). Volunteers participating in the free-living part of the study wore both devices simultaneously on their thigh for at least one typical week- or weekend day.

After the health screening and informed consent were obtained, participants were shown how to install and subscribe to the smartphone app before they were given the VitaBit device.

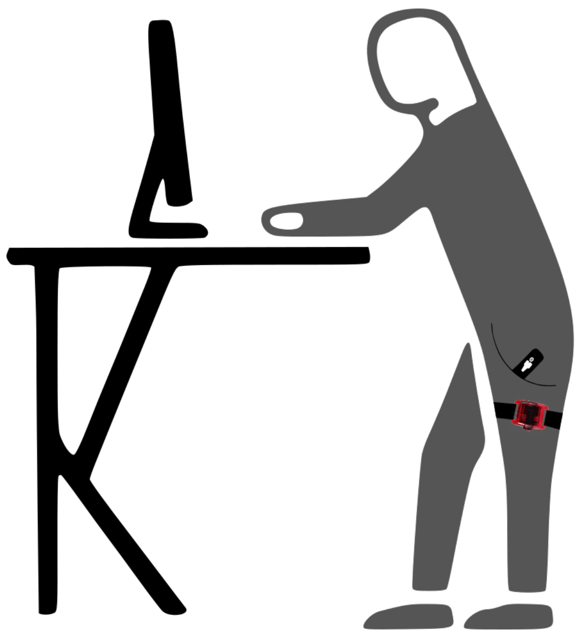

Figure 1. Illustration of wearing locations when wearing both devices simultaneously.

Validity of the VitaBit in a controlled setting

The lab protocol consisted of three different parts. In the first part (see laboratory part 1), the focus was on the distinction between the three activity postures: sitting, standing, and pre-determined paces of walking indicated by a digital metronome. Transition and acceleration periods between the posture changes were excluded from the analyses. The second part (see laboratory part 2) concentrated on performance values with (laboratory part 2a) and without (laboratory part 2b) transitions between posture changes (e.g., sitting to standing; walking to sitting) and on somewhat natural, individual activity paces. A transition interval was defined as the 30 s before and after posture changes, starting or ending with a transition of maximum 5 s. Since the third part (see laboratory part 3) was dedicated to the accelerations of sitting down and getting up, participants performed those transitions in three different paces. The sitting and standing periods following those transitions were analyzed.

Starting times of the three laboratory parts were noted by the researcher. The time remaining before the beginning of an upcoming activity was read aloud and counted down. After following the observation protocol, volunteers were to synchronize the VitaBit sensor with their VitaBit application on their phones.

<u>Laboratory part 1—Distinction between sitting, standing, and walking</u>

In laboratory part 1, participants followed a randomized protocol of the three postures: sitting, standing, and standardized paces of walking activity (walking 80 beats per minute (bpm), 100 bpm, 120 bpm, jogging 140 bpm). Every activity was allocated to one of the six periods of 3 min each, where the first and the last minute served as transition or recovery periods and the minute in the middle of the interval was analyzed. Laboratory part 1 yielded 6 min of data per participant (Figure 2).

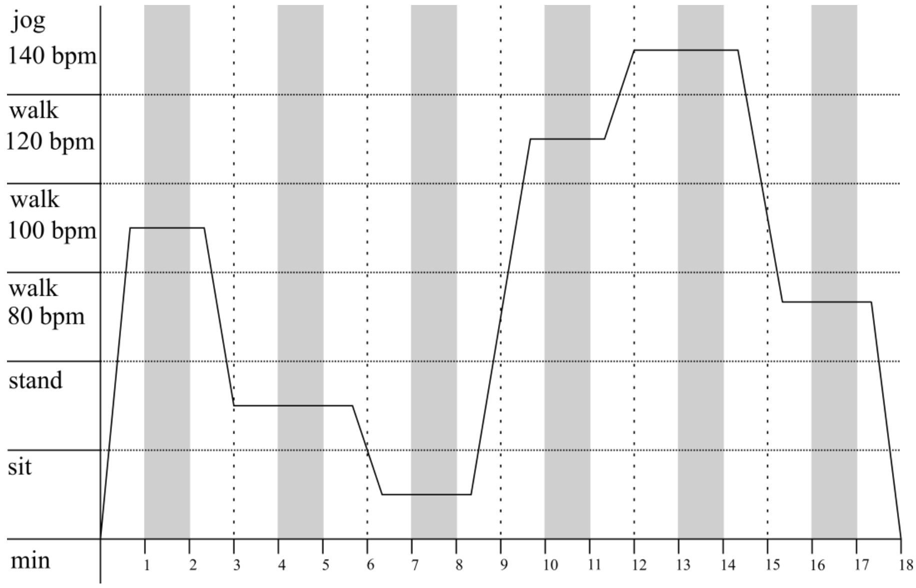

Figure 2. Laboratory part 1: Example protocol of activity distribution as a function of time. Every activity is randomly allocated to one of the six periods of 3 min. While white areas are the time slots in which participants performed transitions; gray areas depict the windows of analysis.

<u>Laboratory part 2—Influence of transitions and natural paces on validity</u>

In order to generalize to all individual walking paces in laboratory part 2, participants were instructed to walk according to their own pace. Furthermore, we aimed to test whether an inclusion of all periods including posture transitions (laboratory part 2a), as occurs in daily life tracking, would yield a difference compared to when we excluded transitions (laboratory part 2b). Participants were instructed to perform each of the activities (sitting, standing, walking slowly, rapidly, and jogging) for 2 min before hearing a count-down of 10 s indicating the upcoming activity. Including all transitions, laboratory part 2a produced 10 min of data per participant. Depending on the protocol's order of postures (e.g., walk rapidly, walk slowly, *transition,* stand, *transition,* sit, *transition,* jog) and, thus, the number of transitions to be excluded, laboratory part 2b revealed 6 to 8 min of data per participant (Figure 3).

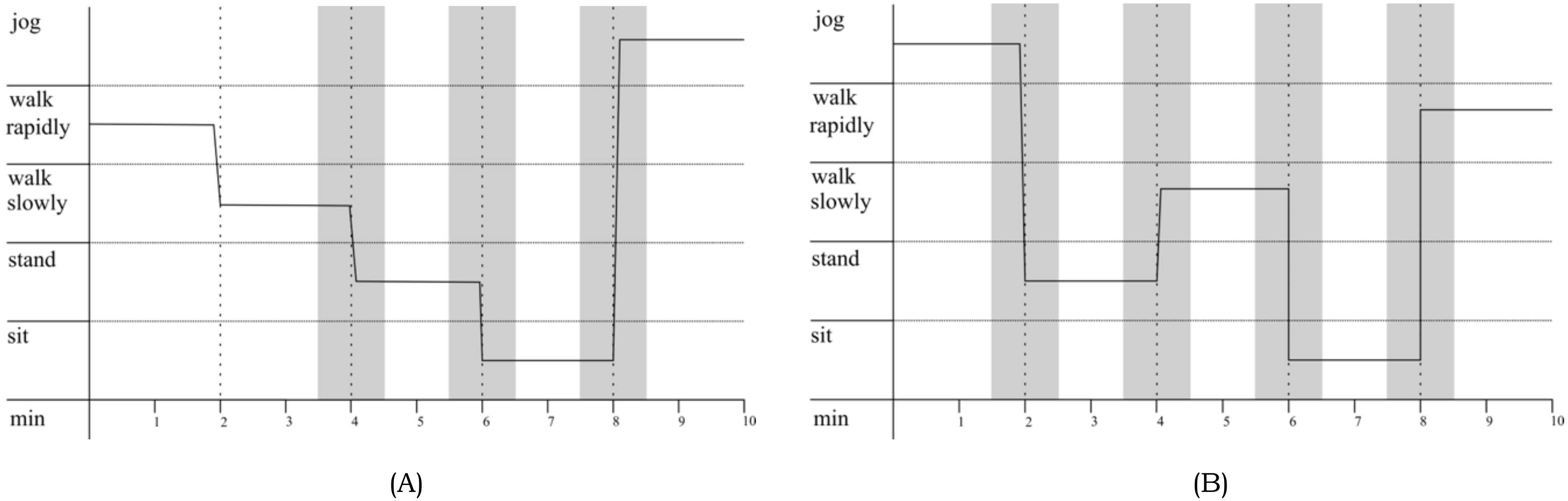

Figure 3. Laboratory part 2: Examples of two different possible activity protocols as a function of time. Thirty-second periods before and after posture changes within the laboratory part 2 are depicted as transition periods, illustrated by the gray areas. It becomes clear that the activity randomization for some participants yields three or fewer transitions (A), while for others it yields four transitions (B). The analysis of laboratory part 2 including all transition periods is referred to as laboratory part 2a and both, the white and the grey marked periods are analyzed. Laboratory part 2b refers to the same observation protocol with the transition periods excluded from the analysis.

Laboratory part 3—Sitting down and standing up: The influence of different speeds

Since the VitaBit algorithm distinguishes between sitting and standing in case there is no walking detected, laboratory part 3 challenged the device by including slower accelerations. Participants were instructed to take no more than 30 s for their posture changes, which were sitting down or getting up for 1, 2, or 3 s. These transition times were then followed by at least 30 s of standing or sitting, which were the objects of analysis. Each pace of sitting down and getting up was performed twice, resulting in 6 min of data per participant after exclusion of transitions (Figure 4).

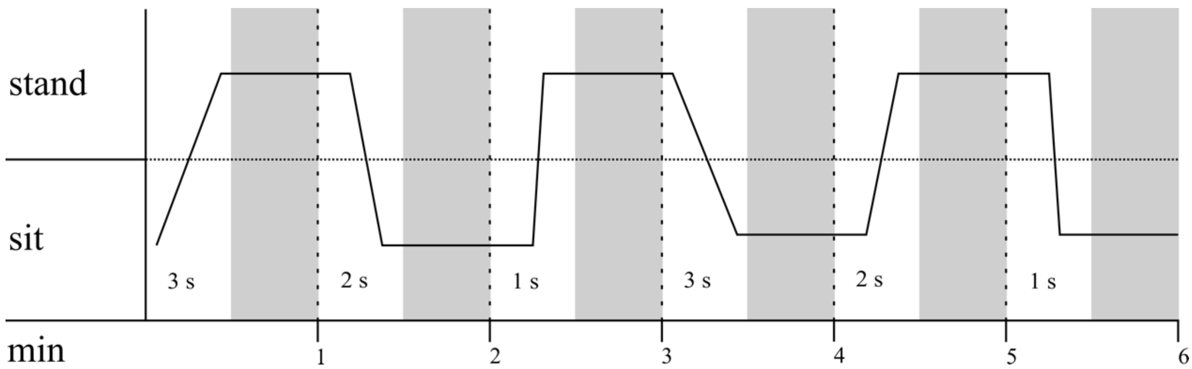

Figure 4. Laboratory part 3: Example of possible activity protocol of the first half of this laboratory part. Process is portrayed as a function of time. Thirty-second periods allocated for the participants' posture changes in one of the three different speeds (1, 2, and 3 s) were excluded. The validity of sitting and standing after the participants had performed their transitions are depicted by the gray areas.

Validity of the VitaBit in a free-living condition

For the free-living study, the ActiGraph with a sampling rate of 30 Hz served as a criterion measurement and participants were instructed to wear both the VitaBit and the ActiGraph at the same time. The ActiGraph is a tri-axial MEMS accelerometer and measures 4.6 cm × 3.3 cm × 1.5 cm. With the help of an elastic strap, it can be placed around the wrist, waist, ankle, or thigh (Actigraph). Although the ActiGraph was already found to be a valid detector for sitting, standing, and walking (Feehan, Goldsmith, Leung, & Li, 2016; Kozey-Keadle et al., 2011; Peterson, Sirard, Kulbok, DeBoer, & Erickson, 2015), different inclinometer algorithms, wearing locations, and performance calculations, respectively, make adequate judgment for our purposes difficult. Therefore, a laboratory sub-study was conducted for two purposes: determining reference performance values (e.g., whether the free-living sensitivity of the VitaBit with ActiGraph as the criterion measurement was equal to the laboratory sensitivity) and revealing the eligibility of the ActiGraph as criterion measurement tool. In the laboratory sub-study, participants wore the ActiGraph as well as the VitaBit device and followed the same protocol as in the VitaBit laboratory conditions.

For the free-living condition, the participants wore the ActiGraph on their thigh (Charlotte L Edwardson et al., 2016) while wearing the VitaBit in their trouser pockets or, if no or only loose pockets were available, attached to a garment around the same position, on at least one typical week- or weekend day. Participants were asked to synchronize the VitaBit sensor with their VitaBit application on their phones after they wore the trackers in their daily lives.

Data analysis

The VitaBit firmware uses a unique algorithm to classify 30-second periods into the categories of sitting, standing, walking and idle data, according to the three-dimensional acceleration data. The researcher exported the raw activity data as .csv files. Each row was dedicated to a certain 30-second period (in UTC time zone) of a user (encrypted as user identifier) indicating the activity as a Boolean variable (e.g., sitting = yes, standing = no, walking = no). The ActiGraph acceleration data were cleaned and converted into activities using the proprietary wearing time validation and the inclinometer function of the ActiGraph software (ActiLife 6.11.9., ActiGraph, Pensacola, FL, USA) (Clemes et al., 2012). Data were further cleaned and adapted to the observation protocols as well as to the VitaBit output using the "PhysicalActivity" package (Choi, Liu, Matthews, & Buchowski, 2011) and general functions in R (R Development Core Team, 2017). In the free-living part, the data from those days were excluded if the participant wore both trackers for less than 5 h per day in order to make adequate device comparisons. Furthermore, if one of the trackers did not register a 30-second period for technical reasons, this period was excluded, hence all analysis are based on merged data. In the laboratory study, 14 datasets of 30 s were not tracked by VitaBit due to late initialization and were excluded. In the free-living study, 3617 of the 33,786 datasets were not tracked by the VitaBit while being tracked by the ActiGraph. Among the data not detected by the VitaBit in the free-living part, 464 datasets at the beginnings and ends of the wearing days are likely due to non-wearing or late initialization of the VitaBit device, and 2895 of the non-tracked datasets were due to wearing only the ActiGraph but not the VitaBit device. Therefore, 258 datasets (0.8%) that were excluded in the free-living part are unexplained lapses of the VitaBit.

Since the ActiGraph displayed the data in second-to-second periods while the VitaBit presented them in 30-second periods, the multiple ActiGraph activities of some 30-second periods needed to be reduced to one single activity. Instead of excluding those ambivalent intervals and, thus, excluding critical transition times, priority was given to the most dominant ActiGraph activity. Therefore, the activity of a 30-second period would constitute the ActiGraph activity performed for the longest time during these 30 s. In case two activities (e.g., sitting, and standing, both for 15 s) or all three activities (e.g., sitting, standing, and walking, all for 10 s) dominated, priority was allocated to sitting, then to standing, and last to walking. For example, 8 s sitting, 11 s standing, and 11 s walking would reveal standing. Those ambivalent situations occurred in 13 out of 1789 (0.73%) periods for the sub-study and in 333 out of 33,785 (0.99%) periods for the free-living periods.

After synchronization of VitaBit with the direct observation protocol data and the ActiGraph data, the performance values, as indicated in Equations (1)–(4), were calculated for each of the three laboratory parts and for each of the three activities on the basis of positives and negatives (Table 1) of all 30-s periods using R (R Development Core Team, 2017). More precisely, sensitivity indicates the percentage of correctly detected activity (e.g., how often, if a person is sitting, this is detected by the device), while specificity refers to the percentage of correctly detected negatives (e.g., how often, if a person is NOT sitting—hence standing or walking—this is detected as non-sitting). Positive (precision) and negative predictive rates indicate the proportion of correctly detected activities (and negatives) among all detected activities. For instance, if the VitaBit displayed the participant as sitting, how much was the participant actually sitting?

Sensitivity = (True Positives)/(True Positives + False Negatives) (1)

Specificity = (True Negatives)/(True Negatives + False Positives) (2)

PPR = (True Positives)/(True Positives + False Positives) (3)

NPR = (True Negatives)/(True Negatives + False Negatives) (4)

Table 1. Confusion matrix for the example of sitting compared to direct observation.

		True condition	
		Observed sitting	**Observed non-sitting (standing or walking)**
Prediction condition	**Detected sitting by VitaBit**	True Positive (TP)	False Positive (FP)
	Detected non-sitting by VitaBit (standing or walking)	False Negative (FN)	True Negative (TN)

Since the ActiGraph as a criterion measurement for the free-living part did not reveal perfect validity, a new free-living activity distribution was estimated based on the ActiGraph precision values obtained during the sub-study. For instance, if a person was actually standing but not detected as such by the ActiGraph *(100% − PPR_standing_ActiGraph)*, the ActiGraph sometimes detected sitting *(Standing_As_Sitting)* or walking *(Standing_As_Walking)* instead. Among all sitting detection, "Standing_As_Sitting" is, therefore, the part, which is, according to the laboratory sub-study, actually standing. Hence, all sitting detection of the ActiGraph can be divided into correctly detected sitting *(PPR_sitting_ActiGraph)*, in actual standing that was misdetected as sitting, as well as in actual walking that was misdetected as sitting. If we calculate all those actual activity portions for each detected activity based on the sub-study (Figure 5), and multiply the portions by the minutes of detected activities from the free-living part, we get a more likely actual activity distribution (see equations below).

Estimated actual sitting = (PPR_sitting_ActiGraph × Detected_Sitting)
+ ((100% − PPR_standing_ActiGraph) × Sitting _As_Standing × Detected_Standing)
+ ((100% − PPR_walking_ActiGraph) × Sitting_As_Walking × Detected_Walking) (5)

Estimated actual standing = (PPR_standing_ActiGraph × Detected_Standing)
+ ((100% − PPR_sitting_ActiGraph) × Standing _As_Sitting × Detected_Sitting)
+ ((100% − PPR_walking_ActiGraph) × Standing_As_Walking × Detected_Walking), (6)

Estimated actual walking = (PPR_walking_ActiGraph × Detected_walking)
+ ((100% − PPR_sitting_ActiGraph) × Walking _As_Sitting × Detected_Sitting)
+ ((100% − PPR_standing_ActiGraph) × Walking_As_Standing × Detected_Standing), (7)

Results

Laboratory study

In the laboratory condition, 11 volunteers (nine females, two males; mean (SD) age 27.1 (5.8) years; height 172.0 (8.9) cm) participated. All participants followed an observation protocol including on average 5.7 (0.9) min sitting (3 min excluded for one participant due to late initialization of VitaBit), 5.5 (1.5) min standing (5 min excluded for one participant due to late initialization of VitaBit), and 10 min walking. The VitaBit detected 6.3 (2.7), 4.9 (2.6), and 10.0 (0.5) min sitting, standing, and walking, respectively (Table 2).

Table 2. Laboratory: Description of population and activity distributions.

Condition	**VitaBit**		**Direct observation**	
(N = 11)	Mean ± SD	Range	Mean ± SD	Range
Age (years)	27.1 ± 5.8	22–38		
Height (cm)	172.0 ± 8.9	156–181		
Sitting (min)	6.3 ± 2.7	2–11	5.7 ± 0.9 [a]	3–6 [a]
Standing (min)	4.9 ± 2.6	0.5–9.5	5.5 ± 1.5 [a]	1–6 [a]
Walking (min)	10.0 ± 0.5	9–10.5	10.0 ± 0	10–10

The statistical measurements of performance for all laboratory parts (Table 3) ranged from 75.6% (PPR, laboratory part 2) to 98.1% (NPR, part 1) for sitting, from 70.0% (sensitivity, part 2) to 97.3% (specificity, part 1) for standing, and from 92.9% (specificity, part 2) to 100% (specificity and PPR, part 1) for walking. Transitions periods to and from sitting affected measurements of performance for sitting: When excluding transition periods in laboratory part 2b, sensitivity (+8.4%) and PPR (+7.2%) for sitting were improved the most, while the other activities' performance values were affected for 2.3% ± 1.4%.

2

Table 3. Laboratory: performance of the VitaBit with direct observation as criterion measurement.

Laboratory part	**Performance measurement**	**Sitting**	**Standing**	**Walking**
1	Sensitivity [a]	90.9	77.3	98.9
	Specificity [b]	95.5	97.3	100
	PPR [c]	80	85	100
	NPR [d]	98.1	95.5	97.8
2a [e]	Sensitivity [a]	77.3	70	96.2
	Specificity [b]	93.6	95.5	92.9
	PPR [c]	75.6	77.8	95.5
	NPR [d]	94.2	93.3	94
2b [f]	Sensitivity [a]	85.7 (+8.4)	72.7 (+2.7)	97.4 (+1.2)
	Specificity [b]	96.3 (+2.7)	96.5 (+1)	98 (+5.1)
	PPR [c]	82.8 (+7.2)	76.2 (+1.6)	99.1 (+3.6)
	NPR [d]	97 (+2.8)	95.8 (+2.5)	94.2 (+0.2)
3	Sensitivity [a]	90	76.7	-
	Specificity [b]	76.7	90	100
	PPR[c]	79.4	88.5	-
	NPR [d]	88.5	79.4	100
All parts	Sensitivity [a]	85.7	74.6	97.3
	Specificity [b]	91.2	95.1	97.6
	PPR [c]	78.3	84.3	97.3
	NPR [d]	94.5	91.4	97.6

[a] ratio of correctly detected activity and observed activity: TP/(TP+FN); [b] proportion of correctly detected negatives (activity distinct from the concerning activity) and negatives detected by observation: TN/(TN+FP); [c] proportion of TPs within detected activity: TP/(TP+FP); [d] proportion of TNs within detected negatives: TN/(TN+FN); [e] incl. transition periods; [f] excl. transition periods (improvement compared to values from 2a).

Regarding sensitivity, in 14.3%, 25.4%, and 2.7% the VitaBit device did not successfully detect sitting, standing, and walking, respectively. When it did not successfully detect sitting, 72.2% were detected as standing, 27.8% as walking. When it was supposed to detect standing, 96.8% was detected as sitting and 3.2% as walking. For walking, it measured standing in 66.7% of the cases and idle data in 33.3% of the cases.

Free-living condition

Sub-study

Eleven volunteers were invited and followed the protocol of the laboratory sub-study. After two persons dropped out because the VitaBit was worn on the wrong place or did not successfully synchronize with the app, nine (six females, three males) participants (mean (SD) age 27.2 (7.7), height 170.2 (8.1) cm) were included in the analysis. All participants followed an observation protocol including on average 6 min sitting, 5.9 (0.2) min standing (30 s excluded for one participant due to late initialization of ActiGraph), and 10 min walking, where 6.4 (0.9), 6.5 (1.4), and 9.1 (1.4) min sitting, standing, and walking, respectively, were detected by the ActiGraph (Table 4).

Table 4. Sub-study: Description of population and activity distributions.

Condition	**ActiGraph**		**Direct observation**	
(N = 9)	Mean ± SD	Range	Mean ± SD	Range
Age (years)	27.2 ± 7.7	22–47		
Height (cm)	170.2 ± 8.1	156–182		
Sitting (min)	6.4 ± 0.9	6–8.5	6 ± 0	6–6
Standing (min)	6.5 ± 1.4	5.5–10	5.9 ± 0.2 [a]	5.5–6 [a]
Walking (min)	9.1 ± 1.4	6–10	10 ± 0	10–10

Sitting, standing and walking data refer to the average activity performed by each participant in the laboratory sub-study.
[a]0.5 standing minutes were excluded in one participant as the ActiGraph did not detect any data.

ActiGraph performance in all laboratory sub-study parts (Table 5) ranged from 81.8% (PPR, laboratory part 1) to 100% (sensitivity and NPR, part 1) for sitting, from 73.9% (PPR, part 1) to 99.3% (NPR, part 2) for standing, and from 86.1% (specificity, part 1) to 99% (PPR, part 2) for walking. With sensitivity and specificity values ranging from 86.1% to 100%, it was judged as eligible for the criterion measurement in the free-living condition.

Table 5. Sub-study: performance of the ActiGraph with direct observation as criterion measurement.

Laboratory part	Performance measurement	Sitting	Standing	Walking
1	Sensitivity [a]	100	94.4	86.1
	Specificity [b]	95.6	93.3	97.2
	PPR [c]	81.8	73.9	98.4
	NPR [d]	100	98.8	77.8
2a [e]	Sensitivity [a]	97.2	97.2	91.7
	Specificity [b]	97.9	95.1	98.6
	PPR [c]	92.1	83.3	99
	NPR [d]	99.3	99.3	88.8
2b [f]	Sensitivity [a]	100 (+2.8)	100 (+2.8)	90.1 (−1.6)
	Specificity [b]	97.3 (−0.6)	94.7 (−0.4)	100 (+1.4)
	PPR [c]	88 (−4.1)	76 (−7.3)	100 (+1)
	NPR [d]	100 (+0.7)	100 (+0.7)	82 (−6.8)
3	Sensitivity [a]	90.7	88.7	-
	Specificity [b]	88.7	90.7	100
	PPR [c]	89.1	90.4	-
	NPR [d]	90.4	89.1	100
All parts	Sensitivity [a]	94.4	92.5	89.4
	Specificity [b]	95.5	93.8	99.1
	PPR [c]	88.7	84.6	98.8
	NPR [d]	97.9	97.1	91.8

[a] ratio of correctly detected activity and observed activity: TP/(TP+FN); [b] proportion of correctly detected negatives (activity distinct from the concerning activity) and negatives detected by observation: TN/(TN+FP); [c] proportion of TPs within detected activity: TP/(TP+FP); [d] proportion of TNs within detected negatives: TN/(TN+FN); [e] incl. transition periods; [f] excl. transition periods.

PPR: When the ActiGraph device detected sitting, standing, and walking, respectively, 11.3%, 15.4%, and 1.2% was misclassified. When it measured sitting while a person was not, for 46.2% the person was standing *(Standing_As_Sitting)*, and for 53.8% walking *(Walking_As_Sitting)*. When it misdetected standing, 33.3% was actually sitting *(Sitting_As_Standing)*, and 66.6% was walking *(Walking_As_Standing)*. For wrongly measured walking, the participant was standing *(Standing_As_Walking)* in 100% of the cases (Figure 5).

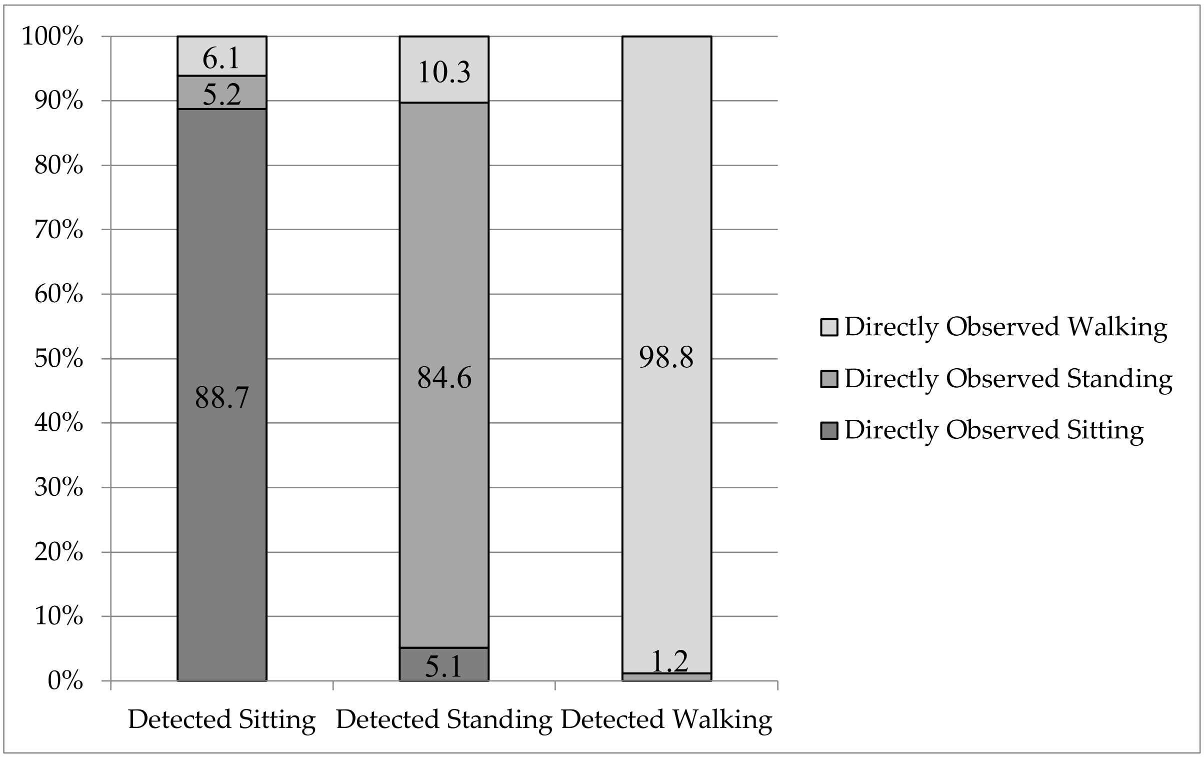

Figure 5. ActiGraph detections and the proportion of actual underlying behaviors.

Free-living

In the free-living condition, seven volunteers (six females, one male; mean (SD) age 34 (10), 167 (9) cm) wore the trackers on three (one) days per person. They wore the two devices on average for 774 (232) min per day (ranging from 323–1102 min per day). According to the ActiGraph, participants' daily sitting time was 489 (171) min, standing time 220 (109) min, and walking time was 64 (40) min. Inferring from the PPR values of the sub-study, it is likely that the participants were actually sitting for 445 (153) min, standing for 212 (94) min, and walking for 116 (49) min. The VitaBit detected them sitting for 444 (200) min, standing for 241 (125) min, and walking for 89 (57) min (Table 6).

Table 6. Free Living: Description of population and activity distributions.

Condition	**VitaBit**		**ActiGraph**		**Estimated actual activity**	
(N = 7)	Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range
Age (years)	34 ± 10	25–49				
Height (cm)	167 ± 9	155–181				
Matched wearing time (min)	774 ± 232	323–1102	774 ± 232	323–1102	774 ± 232	323–1102
Sitting (min)	444 ± 200	165–850	489 ± 171	272–912	445 ± 153	243–815
Standing (min)	241 ± 125	44–461	220 ± 109	41–397	212 ± 94	49–359
Walking (min)	89 ± 57	7–235	64 ± 40	11–157	116 ± 49	31–210

Sitting, standing and walking data refer to the average activity performed by each participant per day.

The activity distributions of estimated activity and VitaBit corresponded: 57.4% (vs. 57.5% estimated) average sitting, 31.1% (vs. 27.5% estimated) average standing and 11.5% (vs. 15.0% estimated) average activity per day. The VitaBit performance with ActiGraph as criterion measurement (Table 7) deviated from the performance values of the sub-study performance values with ActiGraph as reference value (Appendix B). The performance during free-living conditions ranged from 72.6% (NPR; sub-study: 97.9%) to 89.8% (PPR; sub-study: 88.7%) for sitting, from 62.8% (PPR; sub-study: 84.6%) to 87.1% (NPR; sub-study: 97.1%) for standing, and from 47.9% (PPR; sub-study: 98.8%) to 96.8% (NPR; sub-study: 91.8%) for walking.

Table 7. Free living: performance of the VitaBit with ActiGraph as criterion measurement.

Performance measurement	Sitting	Standing	Walking
Sensitivity [a]	81.5	68.7	66.0
Specificity [b]	84.0	83.9	93.5
PPR [c]	89.8	62.8	47.9
NPR [d]	72.6	87.1	96.8

[a] ratio of correctly through the device detected activity and activity from observation protocol: TP/(TP+FN); [b] proportion of correctly through the device detected negatives (activity distinct from the concerning activity; does not necessarily need to assess the same activity than being observed) and all negatives detected by observation: TN/(TN+FP); [c] proportion of TPs within detected activity: TP/(TP+FP); [d] proportion of TNs within detected negatives: TN/(TN+FN).

Discussion

Next to PA measurements, objective measurements of SB are essential to counter its detrimental effects, whether as a monitoring tool for the end user, or as a tool to improve interventions and refine recommendations. The major finding of the laboratory study is that the VitaBit is a specific and precise (PPR) tool to distinguish between sitting, standing, and walking modes. Inferring from direct observation, this applies for sitting still, standing, and regular walking. The performance of the VitaBit with the ActiGraph as criterion measurement and calculated on a minute-by-minute base in the free-living condition is low compared to the sub-study. Yet, both trackers show very similar activity distributions. On a day-to-day basis and for normal sitting, standing, and walking, this makes the VitaBit eligible for measuring SB and its antagonist behaviors and it can be used as a low-cost and user-friendly tool for developing, monitoring, and improving SB change programs.

In the laboratory study, it was found that VitaBit was especially sensitive for walking and sitting. For instance, if the user is not sedentary, over 91% is indeed not displayed as sitting, similar to the value of 95.5% of the ActiGraph. Moreover, the distinction between walking and non-activity of over 97% was higher compared to the ActiGraph output. Therefore, the time of walking or other activities can be trusted, while the remainder concerning the distinction between sitting and standing is still questionable. The sensitivity of standing detection showed the lowest performance in the laboratory condition, while the PPR of standing was the lowest value for the ActiGraph according to the sub-study. Nevertheless, the value of over 70% for accurately distinguishing standing still from sitting can be considered high, since other accelerometer studies overcome this issue by considering standing as SB (Boerema, Essink, Tönis, van Velsen, & Hermens, 2015; Peterson et al., 2015). If we consider the activity distribution and not the minute-by-minute comparison, the interpretation of results is more positive: Since the specificity of walking was very high, it is likely that the VitaBit indicates sitting as the remainder of non-detected standing. Similarly, if sitting is not detected it is likely displayed as standing, revealing at least partly compensated daily sitting and standing accumulations. This is in accordance with the very similar activity distributions of the VitaBit and direct observation in the laboratory part.

The daily activity distributions of the VitaBit compared to the ActiGraph and estimated activity distribution deviate minimally. This is in accordance with former validation studies examining other wearable monitors (Clemes et al., 2012; Kozey-Keadle et al., 2011; Peterson et al., 2015). Nevertheless, the free-living performance values seem quite low calculated on a minute-to-minute base, while the reference laboratory sub-study of VitaBit performance with ActiGraph as criterion revealed higher performance values (e.g., sensitivity: 71.4% sitting, 71.8% standing, 96.9% walking; Appendix B). It is possible that the low free-living tracker correspondence is due to alternative behaviors such as car driving, cycling, or active sitting and to more transitions between postures, revealing different device outcomes caused by different firmware algorithms or high- and low-pass filters of the VitaBit in comparison to the ActiGraph. Therefore, the results from the laboratory study and the sub-study of (at least one of) the devices are likely not directly transferable to free-living behaviors.

Despite very high sensitivity values for sitting of other devices of around 99.7% (Activpal) and 95.1% (ActiGraph GT3X), the sensitivity values of 85.7%

(laboratory condition) and 81.5% (free-living study) for a low-budget and easy-to-deploy sitting monitor with user-friendly software are satisfactory (Grant, Ryan, Tigbe, & Granat, 2006; Kozey-Keadle et al., 2011). Consequently, researchers will need fewer resources for getting and cleaning data and might face fewer compliance issues from their study participants. Furthermore, the current study performed a minute-wise comparison and challenged the VitaBit device by including all transitions and direct observation. Besides relatively high performance values, the individual benefits from the VitaBit tool through their entire behavioral change process. This encompasses the (autonomous) monitoring process, short- and long-term goal setting, and overcoming motivational or social hurdles with the help of individualized feedback from a coach or competition with others. Some of these features can be used if a user joins an environment, which can be done anonymously without sharing personal information. Those factors are often summarized as tailoring and user support and can increase program engagement, and therefore behavioral change (Michie, Yardley, West, Patrick, & Greaves, 2017).

Since the VitaBit is based on accelerations and smaller people's thighs cover shorter transition distances when sitting down or getting up, the device's performance might depend on subject height (results not reported: this statement is based on preliminary findings of a primary performance comparison between shorter and taller subjects). Furthermore, the population on average met the current sitting and standing recommendations (John P Buckley et al., 2015). Therefore, replication studies are needed to confirm our results. Although we "challenged" the VitaBit with tight transition times (laboratory part 2), slow sitting–standing transitions (laboratory part 3), and the requirement to distinguish between standing still and sitting, we observed a limited number of activities. For minute-by-minute values, as opposed to activity distribution, the laboratory findings can, therefore, only be applied to daily life activities that are not specific, such as active sitting. We recommend a direct observational free-living study or a laboratory study with a wider activity range (Boerema et al., 2015; Kozey-Keadle et al., 2011).

Our findings support the usage of the VitaBit device for research, behavioral change specialists, as well as for the individual who aims for a healthier sit–stand–walk pattern. The VitaBit constitutes a compromise between best-practice, highly sensitive SB trackers currently successfully applied in research and commercially available PA trackers effectively used in PA interventions (Atkin et al., 2012; Dominick et al., 2016; Gomersall et al., 2016; Guitar, MacDougall, Connelly, & Knight, 2018; Imboden et al., 2017).

Since the VitaBit shows high performance on a minute-by-minute basis, the device is a valid tool to detect even slight sedentary interruptions. Therefore, sedentary pattern measures, such as number of sitting bouts or breaks per sedentary hour, can be assessed and, with the help of a combining algorithm, such as the VitaBit score, be validated against health indicators (e.g., glucose or insulin levels). Hence, the current lack of a globally accepted and validated sedentary pattern recommendation could be overcome, enabling tailored suggestions such as “interrupt your sitting every hour for at least 2 min of walking to achieve a significant health boost today.” In accordance, we suggest a future validation study including the step count tool of the VitaBit to investigate putative differences between activity levels when interrupting sitting.

Finally, this study can be used to improve the VitaBit device. One suggestion to improve the sit vs. stand distinction could be to implement a gyroscope in addition to the accelerometer. This would reveal a more stable, absolute system of coordinates as a reference, and produce less acceleration-caused confusion for activities such as car driving or active sitting. Nevertheless, this would increase the device’s power consumption and the producer would again arrive at a trade-off between accuracy and user-engagement factors.

Appendix A. PAR-Q (Physical Activity Readiness Questionnaire)

Please read the questions carefully and answer each one honestly: check YES or NO.

	YES	NO
1. Has your doctor ever said that you have a heart condition and that you should only do physical activity recommended by a doctor?		
2. Do you feel pain in your chest when you do physical activity?		
3. In the past month, have you had chest pain when you were not doing physical activity?		
4. Do you lose your balance because of dizziness or do you ever lose consciousness?		
5. Do you have a bone or joint problem (for example, back, knee or hip) that could be made worse by a change in your physical activity?		
6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?		
7. Do you know of any other reason why you should not do physical activity?		

If you have answered "Yes" to one or more of the above questions, consult your physician before engaging in physical activity. Tell your physician which questions you answered "Yes" to. After a medical evaluation, seek advice from your physician on what type of activity is suitable for your current condition.

Appendix B. Sub-Study Comparing ActiGraph and VitaBit

Table A1. Sub-study: Description of population and activity distributions.

Condition	**VitaBit**		**ActiGraph**	
(N = 7)	Mean ± SD	Range	Mean ± SD	Range
Age (years)	24.9 ± 2.5	22–29		
Height (cm)	168.6 ± 7.9	156–181		
Sitting (min)	6.1 ± 2.1	2–8.5	6.5 ± 1.0	6–8.5
Standing (min)	5.6 ± 2.0	3–9.5	6.1 ± 0.4	5.5–7
Walking (min)	10 ± 0.4	9.5–10.5	9.4 ± 0.9	7.5–10

Activity values based on most accurate values per situation. Observations for laboratory data and ActiGraph measurements for free-living data. Sitting, standing, and walking data refer to the average activity performed by each participant per day.

Table A2. Sub-study: performance of the VitaBit with ActiGraph as criterion measurement.

Laboratory Part	Performance Measurement	Sitting	Standing	Walking
1	Sensitivity [a]	66.7	80	98
	Specificity [b]	98.5	95.7	81.8
	PPR [c]	92.3	80	89.3
	NPR [d]	91.5	95.7	96.4
2a [e]	Sensitivity [a]	66.7	66.7	96.2
	Specificity [b]	91.8	95.5	88.3
	PPR [c]	69	80	91.7
	NPR [d]	91	91.3	94.6
2b [f]	Sensitivity [a]	70	64.7	98.5
	Specificity [b]	95.2	96.6	89.2
	PPR [c]	77.8	78.6	94.3
	NPR [d]	93	93.3	97.1
3	Sensitivity [a]	76.7	72.5	-
	Specificity [b]	72.5	76.7	100
	PPR [c]	75	74.4	-
	NPR [d]	74.4	75	100
All parts	Sensitivity [a]	71.4	71.8	96.9
	Specificity [b]	90.3	91.9	92.6
	PPR [c]	75.6	77.2	90.7
	NPR [d]	88.2	89.5	97.6

[a] ratio of correctly through the device detected activity and activity from observation protocol: TP/(TP+FN); [b] proportion of correctly through the device detected negatives (activity distinct from the concerning activity; does not necessarily need to assess the same activity than being observed) and all negatives detected by observation: TN/(TN+FP); [c] proportion of TPs within detected activity: TP/(TP+FP); [d] proportion of TNs within detected negatives: TN/(TN+FN); [e] including transition periods; [f] excluding transition periods.

CHAPTER 3

Sedentary work in desk-dominated environments: A data-driven intervention using Intervention Mapping

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Abstract

Objectives. Since desk-dominated work environments facilitate sedentary behavior, office workers sit for 66% of their working days and only 8% succeed in interrupting their prolonged periods of sitting within the first 55 minutes. Yet stretches of long and uninterrupted sitting increase the likelihood of several chronic metabolic and cardiovascular diseases. We therefore developed a computer-based app designed to interrupt periods of prolonged sitting among office employees.

Methods. When developing the intervention, we applied the intervention mapping protocol. This approach for the systematic design of theory and evidence-based behavior change programs consists of 6 steps: creation of a logic model of the problem, creation of a logic model of change, program design, program production, design of an implementation plan, and development of an evaluation plan.

Results. Working through all 6 steps has resulted in an individually adaptable intervention to reduce sedentary behavior at work. The intervention, UPcomplish, consists of tailored, half-automatized motivational components delivered by a coach. To register sedentary behavior, the VitaBit (VitaBit Software International BV) toolkit, a wearable accelerometry-based monitoring device, is used. Among others, UPcomplish includes personalized goal setting, tailored suggestions to overcome hurdles, and weekly challenges. The VitaBit toolkit supports the participants to monitor their behavior in relation to self-set goals.

Conclusions. Intervention mapping is a useful protocol not only for the systematic development of a comprehensive intervention to reduce sedentary behavior but also for planning program adherence, program implementation, and program maintenance. It facilitates obtaining the participation of relevant stakeholders at different ecological levels in the development process of the intervention and anticipating facilitators to and barriers of program implementation and maintenance.

Introduction

Frequent and uninterrupted sedentary behavior is highly prevalent among office workers (Clemes, O'Connell, & Edwardson, 2014; Ryan, Dall, Granat, & Grant, 2011) and negatively impacts workers' health and well-being by increasing the risk of noncommunicable diseases such as cardiovascular disease, type 2 diabetes (Biswas et al., 2015; Van Uffelen et al., 2010; Wilmot et al., 2012), obesity (Chau, van der Ploeg, Merom, Chey, & Bauman, 2012), and mental health problems (Hamer & Stamatakis, 2014; Voss, Carr, Clark, & Weng, 2014). This is reflected in the higher mortality rates among office workers as compared with those in more active occupations (Chau et al., 2015). Sedentary behavior is defined as sitting, lying, or reclining awake behaviors with low-energy expenditures (≤1.5 metabolic equivalents) (Tremblay, Aubert, et al., 2017). Compensating for the negative effects of sitting time by meeting the recommended levels of physical activity may not be possible (Bankoski et al., 2011; Ekelund et al., 2016; Hamilton et al., 2008; Pandey et al., 2016; Thorp et al., 2011). Moreover, the accumulation of long uninterrupted sitting bouts and/or a daily sitting time of more than 10 hours has been defined as an unhealthy sitting pattern resulting in increased metabolic risk (Bankoski et al., 2011; Healy et al., 2008). Research suggests that prolonged sitting should be interrupted by bouts of light to moderate physical activity (Dunstan et al., 2012; Healy et al., 2008) and standing (Gupta et al., 2016; Owen et al., 2011).

Few studies described the long-term positive effects of interventions to reduce sedentary behavior. Interventions mostly incorporated multiple behavior change methods targeting multiple behavioral determinants (Gardner et al., 2016; Stephenson et al., 2017). Behavior change methods are defined as "general techniques or processes that have been shown to be able to change one or more determinants of behavior" and the behavior, if parameters for use are respected (Bartholomew Eldredge et al., 2016; Kok et al., 2016). For instance, behavior change methods providing information about health consequences and self-monitoring help build the attitude required to decide to change; instructions about how to perform the behavior and social support help build the self-efficacy required to translate the intention into behavior. Establishing a clear link between the identified determinants of behavior and behavior change methods targeting these determinants is a key component of effective behavior change, according to the intervention mapping (IM) protocol (Bartholomew Eldredge et al., 2016). Worksite physical activity interventions designed using IM have revealed positive long-term effects (Coffeng et al., 2014; Kwak et al., 2010; McEachan et al., 2008). However, current effective sedentary behavior interventions are quite cost-intensive requiring a personal coach and/or environmental changes (McEachan et al., 2008) (Coffeng et al., 2012; Kwak et al., 2007). This paper describes the systematic development of a low-cost data-driven worksite sedentary behavior intervention designed with the IM protocol.

IM is a framework for planning intervention development, implementation, and evaluation with six iterative steps. In each step, the program designer applies findings from theory, evidence, and their own research: (1) conducting a needs assessment, (2) stating program outcomes and objectives, (3) designing the program, (4) preparing program production, (5) planning program implementation, and (6) developing an evaluation plan (see Figure 1) (Bartholomew Eldredge et al., 2016; Crutzen & Peters, 2018).

Sedentary behavior can be embedded at both the interpersonal (ie, support by colleagues and managers) and the individual (ie, office workers) level. For example, if an employee would like to interrupt sitting time more often during working hours but is devaluated by their colleagues for not working enough, the new behavior might disappear. Higher levels (ie, organization, community, and society) were not considered in this study for reasons of cost-effectiveness and given that the target high-income Western countries provide sufficient opportunities (such as safe pathways) for individuals to sit less during working hours.

An intervention planning group includes stakeholders who can make relevant contributions to the development, implementation, and evaluation, such as members of the target group and future implementers. This ensures

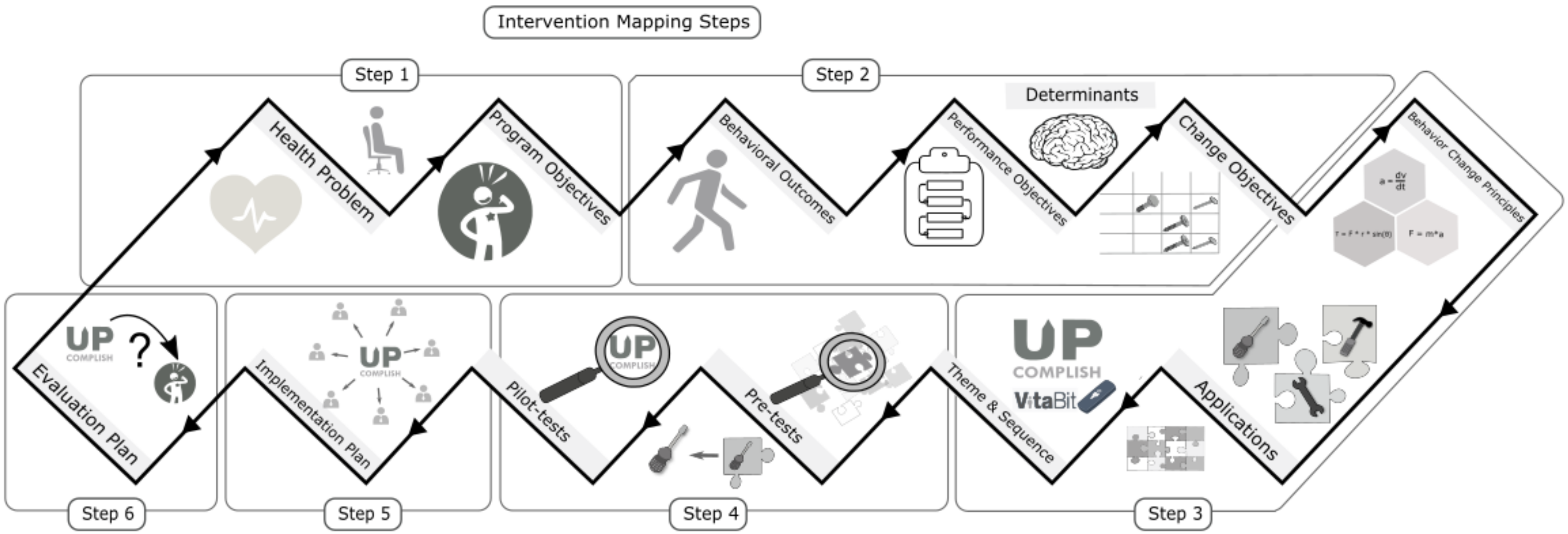


Figure 1. Overview of the steps and products in the Intervention Mapping protocol.

that issues pertinent to the target group are addressed by the intervention or that future implementation issues are anticipated ahead of time (Bartholomew Eldredge et al., 2016).

Computer and smartphone technologies can create platforms that support interactions between individuals, making it possible to exchange both print and more complex multimedia files (eg, a coaching procedure at reduced costs that allows for individually adapted suggestions) (Broekhuizen et al., 2012; Kelders et al., 2012; Schoeppe et al., 2016). Since a permanent reduction of sedentary behavior requires the personal assistance of a professional (Gardner et al., 2016), the main component of our intervention is UPcomplish, which is partly automated, with tailored feedback and motivational support remotely provided by a coach. The VitaBit monitoring toolkit is part of the intervention; participants can monitor their own sedentary behavior related to their personal goals, and the UPcomplish coach can use those data to give almost real-time tailored advice.

In this paper, we describe the systematic development of UPcomplish and the design of the VitaBit monitoring toolkit. IM guided important decisions with regard to objectives, behavior change methods, program production, implementation, and evaluation. The decisions were informed by relevant theoretical and empirical literature including our own empirical research. With UPcomplish and VitaBit, we aim to reduce the number and length of sitting bouts among office workers in the short term (Biswas et al., 2015) and increase the vitality and mental health of employees, as well as minimize their risks for noncommunicable diseases in the longer term.

Methods

All materials and supporting documents are available at the Open Science Framework (OSF) repository https://osf.io/8vu37/?view_only =5c39c5a2e6184ca68eb1ce4c8fa17bfa. The target population consists of office workers in high-income countries (Guthold, Stevens, Riley, & Bull, 2018). The trial was registered with the Netherlands Trial Register [NL7503].

Intervention Mapping steps 1 and 2: Needs assessment and program objectives

The first two IM steps cover problem identification and the logic model of change (problem behaviors and desired behaviors, as well as environmental outcomes). The health problem of sedentary behavior, its impact on quality of life, and the context of the intervention were specified (Figure 1). Individual and environmental factors causing sedentary behavior were identified, and behavioral and psychological outcomes stated for the target group (office workers) and the actors at the interpersonal level (colleagues and managers). Behavioral outcomes often comprise more specific subbehaviors (eg, deciding, planning, monitoring), performance objectives, which are influenced by psychosocial determinants (eg, attitude) consisting of subdeterminants (eg, specific beliefs). Only relevant and changeable determinants were identified. Relevance of a determinant refers to the strength of its association with the outcome behavior; changeability refers to the likelihood that the intervention will influence a change in the determinant (Bartholomew Eldredge et al., 2016). We created a matrix, in which performance objectives constitute the rows, and the relevant and changeable determinants the columns. The cells represent the change objectives and provide detailed and measurable information on who and what will change, providing the basis of our intervention.

Intervention Mapping steps 3 and 4: Program design and production

During IM step 3, we selected behavior change methods based on their suitability to cause change in the determinants that needed to be targeted. These were then translated into practical applications by matching the methods to change objectives considering the parameters of use. We focused on a tailored intervention based on two components (each with several objectives), the VitaBit measurement toolkit and the content of UPcomplish (supplied by the personal coach). We further specified scope and sequence of the program and the program theme. In IM step 4, the practical applications were arranged into a coherent program. Program messages and intervention components were drafted and pilot-tested before being refined and produced.

Intervention Mapping step 5: Adoption and implementation plan

In IM step 5, an adoption, implementation, and sustainability plan was created to maximize the likelihood of maintaining behavioral effects and address program dissemination, structural implementation, and maintenance of the intervention. Relevant stakeholders were identified. Behavioral outcomes were formulated and linked to important determinants. The resulting change objectives were used to map an intervention for adopters, implementers, and maintainers by reapplying IM steps 3 and 4.

Intervention Mapping step 6: Evaluation plan

IM step 6 focuses on planning an evaluation to determine behavioral and health effects and underlying mechanisms of intervention effectiveness. We collected and designed indicators and measures and planned the design and procedure of the evaluation study.

Results

Intervention Mapping steps 1 and 2: Needs assessment and program objectives

Program objectives

Different sedentary behavior parameters have been recommended (John P. Buckley et al., 2015). This lack of consensus is rooted in both differences in predicted health outcomes (ie, coronary heart diseases vs type 2 diabetes) and recommended behavioral outcomes (ie, daily sitting time vs daily amount of light activity). As a behavioral outcome regarding sedentary behavior, we considered the recommended values from three cohort studies investigating diseases relevant to the target group (ie, heart diseases, diabetes, and all-cause mortality) (Chau et al., 2015; Pandey et al., 2016; van der Berg et al., 2016). The program objective includes three subobjectives: reduction in daily sitting time, increase in daily light activity, and attainment of a healthy sitting pattern (including fewer long and uninterrupted sitting bouts). The first two subobjectives were set at a daily sitting time of less than 8 hours per day per person) (Chau et al., 2015; Pandey et al., 2016; van der Berg et al., 2016) and a minimum of 4 hours standing and light activity per day (John P. Buckley et al., 2015).

While not only total sitting time is important but also regular sitting interruptions, there is no direct empirical support for the recommendation of a particular sitting pattern. In order to represent the daily sitting pattern, we propose to square the lengths of the daily sitting bouts and to sum them up (summed squared sitting bouts [SSSB]).

$$SSSB = SitBout_1^2 + SitBout_2^2 + \cdots + SitBout_n^2 = \sum_{1}^{n} SitBout_i^2$$

As this is a new representation, a cutoff recommendation relating this value to health outcomes has not yet been investigated. Therefore, based on our baseline activity data (n=69, see OSF repository), we distinguished between healthy and unhealthy sitting patterns by using the median across all days of SSSB as the cutoff ($18.8 * 10^3$ min^2). We used the median because the first two subobjectives (sitting and light activity time) were met on about 50% of the days. However, this still needs to be investigated with health outcomes. In spite of similar daily absolute and relative sitting times (see OSF repository), the average duration of sitting bouts collected in longer sitting bouts is significantly smaller on healthy SSSB days, while the amount of sitting in shorter bouts seems to be similar (Figure 2). An SSSB below $18.8 * 10^3$ min^2 will constitute a healthy sitting pattern according to this pilot study.

Figure 2 represents different average daily sitting minutes collected in certain bout durations on healthy and unhealthy SSSB days (below and above $18.8 * 10^3$ min^2) in the pilot study. The longer the sitting bout, the less it is represented in a healthy pattern, while time spent in very short sitting bouts is similar between healthy and unhealthy SSSB days. For example, on healthy SSSB days, the individuals spent on average 7.8 minutes of the day in long sitting bouts over 90 minutes (including days without any of these long bouts), while on unhealthy SSSB days, the average time spent in those long bouts was 151.4 minutes. The areas under the curve, therefore, represent the averages of total daily sitting time. Although the average overall sitting time does not differ significantly between healthy and unhealthy SSSB days, this graph clearly shows that on a healthy SSSB day, fewer minutes were collected in longer sitting bouts. We assume that the two sitting patterns differ in terms of health outcome.

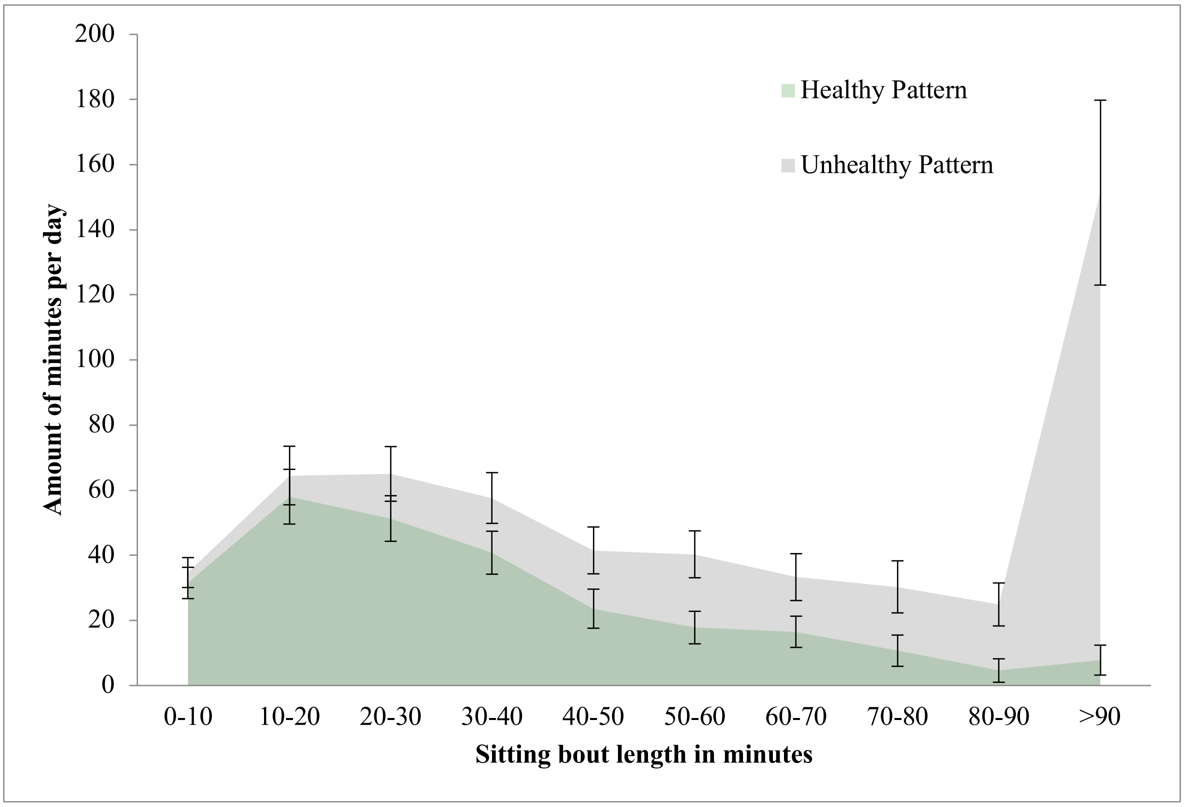


Figure 2. Healthy versus unhealthy summed squared sitting bouts days in the pilot study

The participants in our pilot study met the sitting time objective (maximum 8 hours) with an average of 3.1 days (58.8% of their wearing days), the standing and light activity time objective (minimum 4 hours) with an average of 3.3 days (50.9% of their wearing days), and the SSSB objective (maximum 18.8 * 103 min^2) with an average of 2.9 days (54.0% of their wearing days). All three subobjectives were met on an average of 1.4 days (22.8%). Consequently, we specified the following program goal: Participants should achieve all three recommendations on at least 30% of the wearing days in a week (including weekend days). This, at the baseline measurement, was achieved by 26.1% of the participants (control event rate (Gruijters & Peters, 2017)). We would therefore determine effectiveness by the difference of the proportion of participants who meet the program goal after receiving the intervention compared with baseline.

Behavioral outcomes and performance objectives for the individual office worker

At the individual level, the behavioral outcomes were split into a preintentional motivational phase, building an intention to reduce sedentary behavior and preparing for change, and a postintentional volitional phase, translating the intention into behavior (Schwarzer, 2008). The first behavioral outcome: employees launch a self-regulatory process of controlling their sedentary behavior. This starts with questioning the current behavior and forming an intention to change. It includes monitoring behavior and ends with concrete action planning as indicated by self-set goals. The second behavioral outcome: employees engage in activities in accordance with their previously formulated goals. This focuses on the translation of intentions into behavior by overcoming barriers and actual regular interruptions of sedentary behavior. In addition to this self-regulatory process, other desired behavioral outcomes of the program include establishing good habits and preparing participants for relapses (McEachan et al., 2008; Sniehotta, Presseau, Hobbs, & Araújo-Soares, 2012).

Behavioral outcomes and performance objectives at the interpersonal level

At the interpersonal level, support by colleagues and supervisors is important (Schoeppe et al., 2016). Approval from both stakeholders therefore needs to be encouraged and clearly demonstrated. After colleagues and supervisors have decided to show their support, they can apply different supporting strategies. They could decide to participate in a challenge sharing effective strategies for reducing sitting time, as well as joining in and/or initiate standing or walking meetings (Ball, Bauman, Leslie, & Owen, 2001; Giles-Corti & Donovan, 2003). The support of the supervisors and managers is additionally reflected in the allocation of a room for the kick-off meeting and provision of the funding for the intervention. More information about these two behavioral outcomes can be found in the adoption plan in IM step 5. Supervisors and managers can participate in the program themselves providing similar support to that of the colleagues of the target group (Butterfoss, Kegler, & Francisco, 2008).

Determinants and change objectives at the individual and environmental levels

Empirical evidence from previous sedentary behavior studies was garnered to discover determinants for each performance objective. Since standing is often perceived as being more exhausting than sitting, we included evidence from physical activity research (McEachan et al., 2008). Identified determinants and their synonyms were covered by the reasoned action approach (Fishbein & Ajzen, 2011) and the extended parallel process model (Witte, 1992). The temporal self-regulation theory for physical activity (Hall & Fong, 2015) was considered to facilitate the translation of intentions into actual behaviors.

Attitudes, perceived social norms, and perceived behavioral control have been shown to explain about 33% of the variance of intention to be less sedentary at work, while 37% of the variance of actual sedentary behavior at work is explained through intention (Prapavessis, Gaston, & DeJesus, 2015). Since the act of providing support (at an interpersonal level) is a reasoned action, those determinants were also used for agents at the interpersonal level. At the individual level, perceived susceptibility was added as a determinant. A person might only consider making a change if they feel that the threat of negative health outcomes from too much sitting is likely to impact them (Witte, 1992).

Specific underlying beliefs were used to develop change objectives, informed by qualitative literature (De Cocker et al., 2015; McEachan et al., 2008) and focus group interviews. For example, in order for an individual to participate, the perceived need to be more active (attitude) and the outlook to receive support (injunctive norm) are critical (Bardus, Blake, Lloyd, & Suggs, 2014). The concerning change objective: employees name current and potential serious or immediate negative consequences of their current sedentary behavior. From the temporal self-regulation theory for physical activity, the change objectives related to attitude included the importance of the perceived benefits as being greater and sooner, while the perceived costs were smaller and later. Making those benefits and costs salient at choice time was addressed by the change objectives listed under perceived susceptibility (Hall & Fong, 2015). All change objectives are displayed in the matrices of change objectives (see OSF repository for the matrices and the complete logic model of change). Figure 3 illustrates the logic model of change.

Intervention Mapping steps 3 and 4: Program design and production

Behavior change methods and practical applications

VitaBit provides the basis for monitoring and delivering individual data, while UPcomplish is provided by a coach to help participants improve their sitting pattern by overcoming individual hurdles. Health professionals and vitality coaches from the field will be the implementers of the intervention, using partly automatized components of UPcomplish (IM step 5). The practical applications can be found in the acyclic behavior change diagrams in the OSF directory, and Figure 4 illustrates examples of important practical applications.

Program theme and sequence

The theme of UPcomplish is based on the assumption that behavioral change in a professional setting should not be too invasive but still motivational. Therefore, the main factors are challenge and low invasiveness. UPcomplish consists of the word up, indicating the goal of the program is supporting desk workers to stand up, and the word accomplish, which reflects the challenging character of the intervention. Getting UP will be accomplished.

The initial phase of preparation and kick-off provides the foundation for the relationship between participant and coach. Participants are introduced to the VitaBit toolkit, familiarize themselves with their own behavior, and get

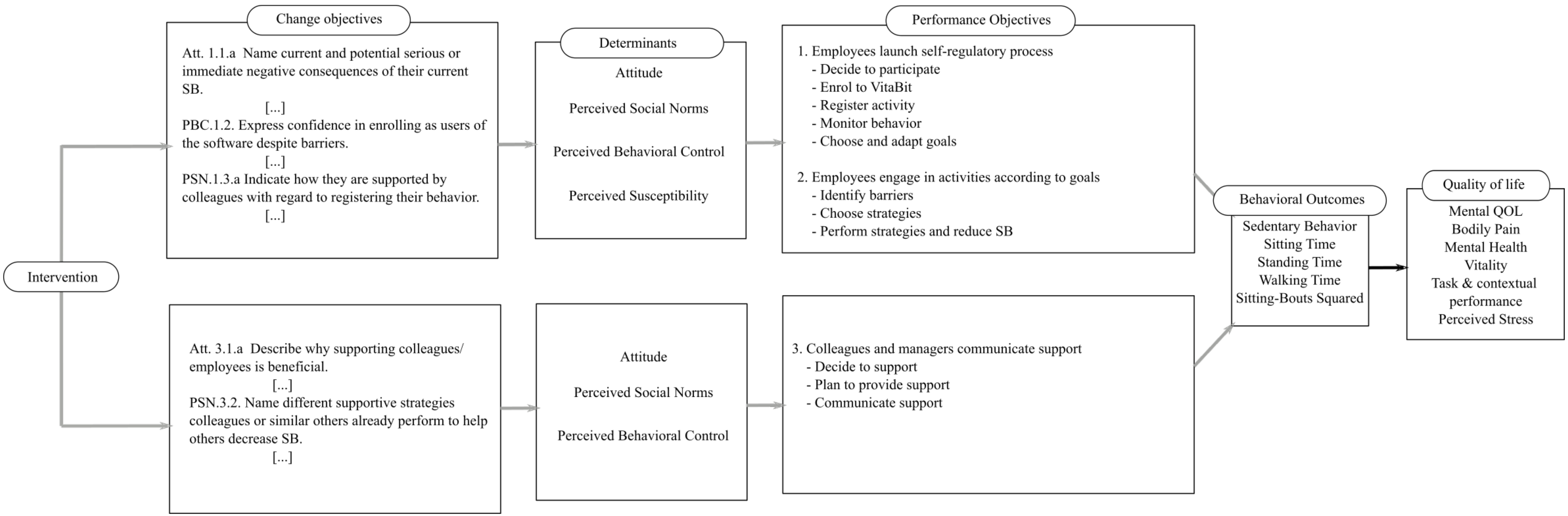


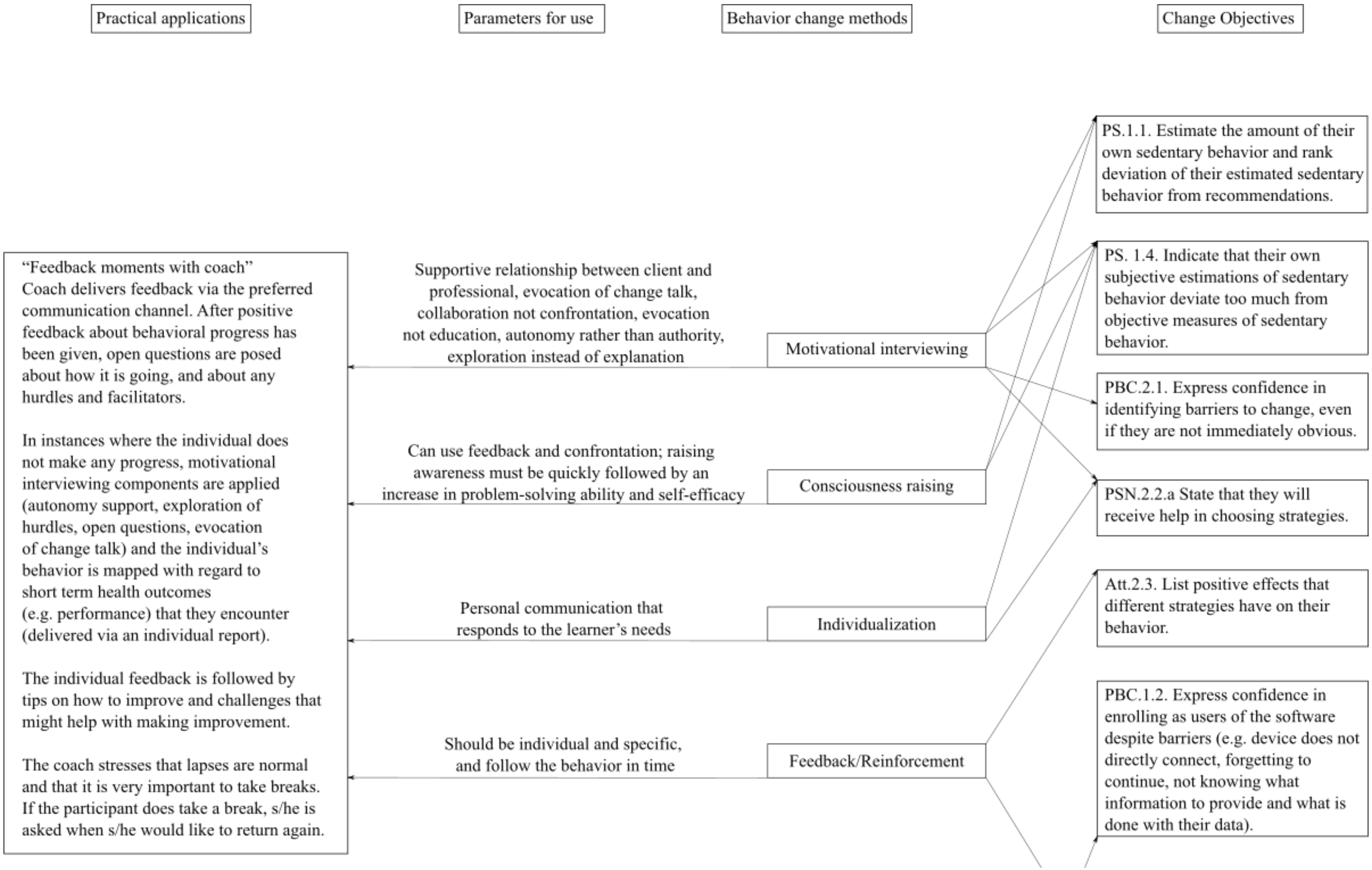
Figure 3. Illustration of the Logic Model of Change

to know the coach. During the kick-off meeting, individualized goals are set, the importance of interrupting sitting is explained, and the preferred communication channel between coach and participant is agreed upon. The baseline phase continues with behavioral and vitality measurements; participants use the VitaBit device for at least 1 week and complete vitality, health, and performance questionnaires including the task and contextual performance subscale of the Individual Work Performance Questionnaire, the Perceived Stress Scale, and the bodily pain, mental health and vitality subscales of the 36-item Short Form Health Survey (S. Cohen, Kamarck, & Mermelstein, 1994; Klein et al., 2016; Koopmans et al., 2014; Ware Jr, 2000) (first of 3 times). During the 3-month trajectory with the coach, participants are provided with activity challenges in biweekly circles. They receive feedback about their behavior 2 times per week and discover facilitators of and hurdles to their behavior through motivational interviewing components. Goals are adjusted after 4 and 8 weeks. In the middle of the intervention, after 6 weeks, participants complete the vitality questionnaire for the second time. In the last 2 weeks, there is a focus on building up habits supported by implementation intentions and the use of buddy systems. At this stage, the vitality questionnaire is completed for the last time (Hagger et al., 2016; Hall & Fong, 2015; McNeill, Kreuter, & Subramanian, 2006). A group report and individual vitality feedback provide an overview of the participant's achievements (see OSF directory).

Pretests of program materials

In order to determine whether the program can be implemented, it needs to be pretested and pilot tested. Pretesting refers to the process whereby specific components of the intervention are tested among the intended population before final production. The goal of pretesting is to safeguard the conditions for effectiveness of the behavior change methods in each component.

Pilot testing is the last evaluation involving all program components, the intended population, and implementers prior to the actual implementation.


Practical applications
Parameters for use
Behavior change methods
Change Objectives
PS.1.1. Estimate the amount of their own sedentary behavior and rank deviation of their estimated sedentary behavior from recommendations.
PS. 1.4. Indicate that their own subjective estimations of sedentary behavior deviate too much from objective measures of sedentary behavior.
PBC.2.1. Express confidence in identifying barriers to change, even if they are not immediately obvious.
PSN.2.2.a State that they will receive help in choosing strategies.
Att.2.3. List positive effects that different strategies have on their behavior.
PBC.1.2. Express confidence in enrolling as users of the software despite barriers (e.g. device does not directly connect, forgetting to continue, not knowing what information to provide and what is done with their data).
"Feedback moments with coach"
Coach delivers feedback via the preferred communication channel. After positive feedback about behavioral progress has been given, open questions are posed about how it is going, and about any hurdles and facilitators.
In instances where the individual does not make any progress, motivational interviewing components are applied (autonomy support, exploration of hurdles, open questions, evocation of change talk) and the individual's behavior is mapped with regard to short term health outcomes (e.g. performance) that they encounter (delivered via an individual report).
The individual feedback is followed by tips on how to improve and challenges that might help with making improvement.
The coach stresses that lapses are normal and that it is very important to take breaks. If the participant does take a break, s/he is asked when s/he would like to return again.
Supportive relationship between client and professional, evocation of change talk, collaboration not confrontation, evocation not education, autonomy rather than authority, exploration instead of explanation
Motivational interviewing
Can use feedback and confrontation; raising awareness must be quickly followed by an increase in problem-solving ability and self-efficacy
Consciousness raising
Personal communication that responds to the learner's needs
Individualization
Should be individual and specific, and follow the behavior in time
Feedback/Reinforcement

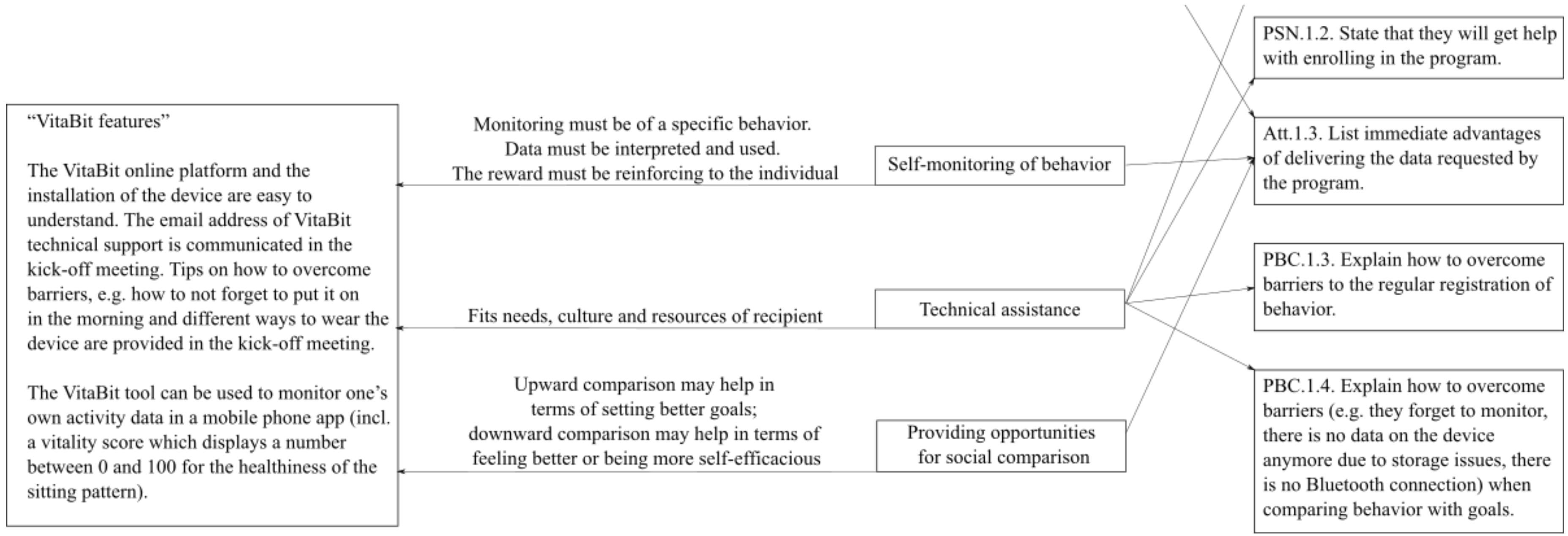


Figure 4. Examples of practical applications

The goal is to assess the acceptability of the entire program and anticipate any problems in implementation (Bartholomew Eldredge et al., 2016).

VitaBit monitoring toolkit pretest

The VitaBit toolkit consists of an accelerometer, mobile phone app, and complementary online platform. These provide the user with tools to monitor their posture patterns with the help of a vitality score (0 = unhealthy, 100 = healthy), set short- and long-term goals, and compare their performance with that of other users. The VitaBit device is a small (3.9 × 1.4 × 0.85 cm, 4.8 g) triaxial wearable accelerometer that monitors sitting, standing, and activity behavior on a half-minute-by-half-minute basis. With regard to sitting, it shows sensitivity and specificity values of 85.7% and 91.2%, respectively (Berninger, Ten Hoor, & Plasqui, 2018).

Before the release of the VitaBit toolkit, over 50 pretesters (exact number was not documented) from potential organizations were allocated the VitaBit device, asked to use the device for as long as they liked, and later contacted to provide feedback. This feedback provided information about functionality, design, and features and was translated into improving software components by the VitaBit development team.

UPcomplish pretest

Initial UPcomplish components were pretested in 11 dispatchers from a German control center. Standing desks were available to these individuals, whose duties mainly involved desk work. A kick-off meeting entailed discussions about the importance of being less sedentary and a short explanation about the intervention and its development. Participants received a weekly progress report. Individual hurdles and facilitators were discussed via their preferred communication channel. Each week, participants received a message in which different performance objectives were addressed, depending on former behaviors and/or reactions to messages (ie, week 1: monitoring behavior; week 2: goal setting; week 3: identifying barriers; etc; see OSF directory). Challenges and other aspects of gamification were not yet included. Two focus group discussions and individual phone calls with participants of this pretest provided feedback about the intervention suggesting that the videos were not watched because they were perceived as being too long, too difficult to download, or too difficult to understand. These video clips were therefore removed from UPcomplish. The kick-off created an atmosphere of trust. However, due to the information about the intervention development being perceived as too lengthy, we decided to shorten the session. The kick-off meeting was also used to help the participants who had not yet tried or succeeded in connecting their device. We decided to split these program components up and call them account creation and pairing the device and that account creation should already be covered before future kick-off meetings to avoid some participants having to wait around. Pairing the device should be handled after the kick-off meeting, in case participants want to directly pair their device with support. The inclusion of challenges and aspects of gamification were not included in this pretest. However, we assumed that these would be attractive and helpful elements. In addition to tailored psychological advice, tailored health advice on individual health outcomes was perceived to be potentially helpful. We decided that motivational interviewing questions should be shortened, and performance objectives addressed more frequently, resulting in more frequent delivery of more concise information. Participants showed interest in the vitality score, which provided them with a value between 0 and 100 of how healthy their sitting pattern was.

Pilot test of UPcomplish

After all adaptations had been made, based on the results of our pretesting, 23 public service desk workers from the Netherlands (5 in the UPcomplish group, who explicitly asked to receive the intervention) took part in our pilot test. After the kick-off meeting, each participant in the UPcomplish group received feedback 2 times per week via their preferred communication channel: individual feedback about goal achievement over the previous week and information regarding sitting patterns on certain weekdays. Furthermore, facilitators of and barriers to sitting less were discussed. Every 2 weeks, participants received gamified challenges. After 4 and 8 weeks, individual goals were revised, if necessary. Summarizing reports completed the intervention. All participants of UPcomplish remained in the program until the end and perceived the coaching to be helpful in terms of reducing sitting time. On average per week, they wore the VitaBit on 74.6% of the days. We observed improvements of sitting, standing, and activity time but cannot interpret them due to the low number of participants and the selectivity of the sample.

Intervention Mapping step 5: Adoption and implementation plan

We expect the managers of our target companies to adopt the intervention, as indicated by the provision of financial funding for the intervention and provision of a room for the kick-off meeting. Additionally, they will supervise and oversee the sustainability of the intervention and its effects. In order to adopt the intervention, the managers first should identify a need to make a decision (eg, determinant: attitude). Second, they should prioritize UPcomplish for individual reasons, such as for an improved reputation of the company (eg, determinant: attitude). Eventually, they should subscribe to the program and continue the subscription for the long run (eg, determinant: perceived behavioral control and attitude) while supervising behavioral maintenance of their employees or institutionalizing the program (Butterfoss et al., 2008).

Personal talks with the management will address diverse underlying buying preferences. A regular report linking average activity and rates of dropout and commitment, among others, to short-term effects on vitality, performance, mental health, and perceived stress will facilitate positive outcome expectancies. A separate study linking the health outcomes to return on investment is in the planning.

Health professionals and vitality coaches from the field are the implementers of this intervention. It is essential that every component is delivered in the suggested tailored and supportive way in order to maintain program fidelity. Completeness will be accomplished if users receive all of the program components. A workshop for data-driven coaching and meetings with the coaches that implement UPcomplish will maximize fidelity and completeness. A coaching portal in the VitaBit dashboard helps the coach to easily supervise their participants by getting an overview of individual activity patterns. Buttons next to the values of the participants make it possible to deliver the coaches' suggestions directly to the relevant participants or to get an overview of their dashboards. Multimedia Appendix 1 shows an example of the coaching portal. The average sitting, standing, and walking parameters for a given period of time are displayed on one page. On the right, the coach can send individual notifications and emails, inspect the individual portal to get more detailed insights into the daily activity behaviors, and create new widgets, such as setting a new goal.

Mobile phone–based workplace sedentary behavior interventions seem to be especially effective in the medium term (3- to 6-month follow-up) if they incorporate several behavior change methods (Stephenson et al., 2017). These include self-monitoring and prompts or cues combined with information about health consequences and information about how to perform the desired behavior. In order to facilitate program sustainability, it is important to tailor the maintenance intervention to the participants who sit the most during their workdays, or, more generally, to those with different motivational profiles, such as a focus on health promotion versus weight loss versus illness prevention (Fukuoka, Lindgren, Mintz, Hooper, & Aswani, 2018; Stephenson et al., 2017). The coaches are encouraged to stress the importance of buddy systems and deliver regular short and precise health information in order to stabilize attitudes about sedentary behavior in the target group. Optional email reminders and health blogs help users to be reminded of the importance of reducing sitting time. Analyzing dropouts in the process evaluation and preventing reasons for future dropouts will help to facilitate program sustainability (Bartholomew Eldredge et al., 2016).

Intervention Mapping step 6: Evaluation plan

We plan to evaluate short-term effectiveness in terms of decreased sitting time, SSSBs, and increased standing and walking time (secondary effects on short-term quality-of-life outcomes) (Dunlop et al., 2015; Hamer & Stamatakis, 2014; Hendriksen et al., 2016) of UPcomplish (effect evaluation).

Furthermore, we will consider whether any program adaptations are needed and what these might be (process evaluations). We will employ a multilevel design with between-subjects and within-subjects factor (measurement moment) comparisons and estimate the intervention's effect in a magnitude of standard deviations (Cohen d) to enable the computation of the number needed to treat (number of people that should receive the intervention for one person to change their behavior sufficiently to meet the criteria specified in the intervention goal) (Gruijters & Peters, 2017). The number needed to treat can be used to calculate the cost of the intervention needed for at least 30% of the participants to achieve all three behavioral outcomes.

From May 2019 until January 2020, we had 200 VitaBit monitors at our disposal. We chose a stepped-wedge design (last week of one group is compared with first week of another group) because a control group (VitaBit only) was not possible considering high expected dropout rates and feasibility issues. Splitting up intervention groups into as many groups as possible would reveal a bigger sample size since some groups could provide data for both the baseline and postintervention measurement. Having five different intervention groups was considered the minimum yet doable number of groups where one group can provide data for the two measurements. The five intervention groups, each comprising 40 participants, start with a time lag of 7 weeks. With an anticipated retention rate of 80%, this yields an analyzable sample size of n=192 (L. A. Waters, B. Galichet, N. Owen, & E. Eakin, 2011). With 192 participants, estimation of this effect size is accurate to about a quarter of the standard deviation (see the OSF repository for details and a flowchart illustrating the design).

The process evaluation is informed by qualitative and quantitative output from surveys and behavioral data and will assess both intervention components and important components of the logic model of change.

Procedure

Groups of 10 to 15 desk workers from random companies in Germany are recruited via email and personal contacts. Potential groups are randomly assigned to one of the intervention groups and informed about the intervention and the measurements before consent is obtained. Each group receives the 12-week intervention and is requested to complete vitality, performance, and mental health questionnaires at 3 points in time. Participants can refuse participation in the intervention and/or the measurements at any times without giving a reason. The evaluation of this intervention including its consent procedure was approved by the Ethical Review Committee, Psychology and Neuroscience, Maastricht University, the Netherlands (ERCPN- 188_11_02_2018). More details can be found in "The Evaluation of UPcomplish: Sample size planning and procedure" in the OSF directory.

Measures process evaluation

All questionnaires can be found in the OSF repository and were translated into German using the back-translation method if no validated German version was available (Brislin, 1970). Table 1 provides an overview of all measurements that are used in the evaluation.

Statistical analyses

Statistical analyses encompass multilevel analyses. For the between-subject comparisons, the outcome variables are centered around baseline company means, and the analyses are nested by calendar week. For the within-subject comparisons, the outcome variables are centered around calendar weeks, and the analyses are nested on the individual level. Analyses are adjusted for possible confounding variables such as company-related variables, gender, or age.

Multilevel linear and logistic regressions are conducted to inspect putative effects of performance objectives and determinants on the continuous primary outcome variables and the dichotomous performance objectives (performed yes/no), respectively.

Table 1. Measurements and example items.

Variable	Measurements and indicators	Items	Example item	Point in time
Intervention characteristics				
Acceptability	Taken from a former evaluation (De Cocker et al., 2015)	18	"The questions within the recommendations were clear."	End
Fidelity	Messages from automated pool divided by total amount of messages sent by the coach	N/A[a]	N/A[a]	End
Reach	Dropout rate; ratio of participants from the intended target group; dose received	N/A[a]	N/A[a]	End
Determinants				
Attitude	Taken from a former evaluation (De Cocker et al., 2015)	6	"Standing and walking around at work is healthy."	Baseline, middle, end
PSN[b]	Taken from a former evaluation (De Cocker et al., 2015)	2	"Standing and walking around at work is encouraged by my colleagues."	Baseline, middle, end
PBC[c]	Taken from a former evaluation (De Cocker et al., 2015)	4	"I am sure that I can stand and walk around at work, even though I feel bad, tired, tense or depressed."	Baseline, middle, end
Perceived susceptibility	Self-created questions to assess perceived susceptibility to improper sitting habits	2	"My daily sitting time is more than what is recommended."	Baseline, middle, end

[a]N/A: not applicable.
[b]PSN: perceived social norms.
[c]PBC: perceived behavioral control.

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Table 1. (continued)

Performance objectives				
PO[d] 1.2 Enrollment as VitaBit user	Proportion of successfully enrolled participants among the ones who agreed to participate	N/A[a]	N/A[a]	End
PO 1.3 Registration of sedentary and antagonistic behaviors	Average of days per week that show VitaBit data for at least 6 hours	N/A[a]	N/A[a]	End
PO 1.4 Monitoring of behavior	Number of days missing before the feedback moments	N/A[a]	N/A[a]	End
Action planning, identifying barriers and facilitators, and support	Numbers and quality of responses to coaching questions/requests	N/A[a]	N/A[a]	End
Sedentary behavior and physical activity				
Objectively measured sitting (30-second periods)	VitaBit measurement toolkit (Atkin et al., 2012; Berninger et al., 2018)	N/A[a]	N/A[a]	continuously
Moderate and vigorous physical activity	German version of the International Physical Activity Questionnaire (short form) (Craig et al., 2003)	max. 6	"During the last 7 days, on how many days did you do vigorous physical activities like heavy lifting, digging, heavy construction, or climbing stairs as part of your work? Think about only those physical activities that you did for at least 10 minutes at a time."	Baseline, middle, end

[a]N/A: not applicable.
[d]PO: performance objective.

Table 1. (continued)

Secondary outcome: quality-of-life				
Task and contextual performance	Two subscales of the Individual Work Performance Questionnaire (Koopmans et al., 2014)	14	“In the past week, I took on extra responsibilities.”	Baseline, middle, end
Stress perception	Perceived Stress Scale (S. Cohen et al., 1994; Klein et al., 2016)	10	“In the last week, how often have you felt nervous and “‘stressed’?”	Baseline, middle, end
Bodily pain	Subscale of the SF[e]-36 health survey (Ware Jr, 2000)	2	“How much bodily pain have you had during the past week?”	Baseline, middle, end
Mental health	Subscale of the SF-36 health survey (Ware Jr, 2000)	5	“How much of the time during the past week have you been a happy person?”	Baseline, middle, end
Vitality	Subscale of the SF-36 health survey (Ware Jr, 2000)	4	“How much of the time during the past week did you have a lot of energy?”	Baseline, middle, end
Covariates: demographic, educational, and job-related variables				
Gender, age, educational level, height, weight, and job-related variables (eg, team size)	Measured by VitaBit during account creation	8	N/A[a]	Baseline
Job tasks	Taken from a former evaluation (De Cocker et al., 2015)	5	“How much on average per day (in %) do you estimate you spend on the following tasks? Phone calls?”	Baseline
Employment status and working times	Self-created questions	2	“How many days do you usually work in a week?”	Baseline

[a]N/A: not applicable.
[e]SF: Short Form Health Survey.

Discussion

This paper describes an IM protocol to develop a computer-based intervention aimed at reducing sedentary behavior at work. A tailored intervention was developed to guide participants step by step through a behavioral change process. The support of both colleagues and supervisors was considered and addressed in additional components. A plan to ensure adoption, implementation, and sustainability was drafted. Finally, we developed an evaluation plan for assessing the effects of the intervention and the mechanisms behind these effects.

Although the IM approach suggests working through all the core processes, not all substeps were performed in our study (Ruiter & Crutzen, 2020), partly due to the fact that additional research (eg, about the necessity of all behavioral substeps [ie, performance objectives]) was still ongoing. Still, we plan to complete a process evaluation that will investigate mechanisms of effectiveness and provide additional information. A second limitation is that members of the target group and managers of companies who might potentially use the intervention (except those working at VitaBit) were contacted too late to be part of the planning group since they were only contacted as part of the pretest and pilot test. Nevertheless, the interest in reducing sedentary behavior seems to be high, and multiple informal talks during the development process with potential adopters, implementers, and people from the target group have revealed valuable insights.

A benefit of the project was the collaboration between scientific research and information technology practice. To facilitate this collaboration, face-to-face and Skype discussions were used to directly exchange ideas and possibilities. In doing so, we also discovered more challenging aspects of collaboration between health promotion and information technology practice. The usage of technical terms on both sides, different priorities during the development process, and balancing act between tailoring and standardization are examples of the challenges we encountered. However, working together allowed for a quick translation of knowledge about behavioral change into practical applications and provides an example that can be applied to other IM procedures (Montag, Duke, & Markowetz, 2016; Smith-Dektor & Young, 2014).

We developed a comprehensive intervention targeting important determinants at three different ecological levels. The development of our intervention was grounded in relevant literature, and multiple theories have been applied. Future evaluation studies should investigate the program effectiveness and further analyze the relevance and utility of single program components.

CHAPTER 4

Bidirectional day-to-day associations of reported sleep duration with accelerometer measured physical activity and sedentary time among Dutch adolescents: an observational study

Berninger, N. M., Knell, G., Gabriel, K. P., Plasqui, G., Crutzen, R., & ten Hoor, G. A. (2020). Bidirectional day-to-day associations of reported sleep duration with accelerometer measured physical activity and sedentary time among Dutch adolescents: an observational study. *Journal for the Measurement of Physical Behaviour* (in print)

Abstract

Objectives. To examine the bi-directional association of sleep duration with proportions of time spent in physical behaviors among Dutch adolescents.

Methods. Adolescents (*n* = 294, 11-15 years) completed sleep diaries and wore an accelerometer (Actigraph) over one week. With linear mixed-effects models, we estimated the association of sleep categories (short, optimal, long) with the following day's proportion in physical behaviors. With generalized linear mixed models with binomial distribution we estimated the association of physical behavior proportions on sleep categories. Physical behavior proportions were operationalized using percentages of wearing time and by applying a compositional approach (CoDA). All analyses were stratified by gender accounting for differing developmental stages.

Results. For males (number of observed days: 345, *n* = 83), short as compared to optimal sleep was associated with the following day's proportion spent in sedentary (-2.57%, p = .03, 95% CI [-4.95, -0.19]) and light-intensity activities (1.96%, p = .02, 95% CI [0.27, 3.65]), which was not significant in the CoDA models. Among females (number of obs.: 427, *n* = 104), long sleep was associated with the proportions spent in MVPA (1.69%, $p < .001$, 95% CI [0.75, 2.64]) and in sedentary behavior (-3.02%, $p < .01$, 95% CI [-5.09, -0.96]), which was replicated by the CoDA models. None of the associations between daytime activity and sleep were significant (number of obs.: 844, *n* = 204).

Conclusions. Results indicate partial associations between sleep and the following day's physical behaviors, and no associations between physical behaviors and the following night's sleep.

Introduction

Suboptimal sleep during adolescence is associated with numerous deleterious outcomes, such as poor physical and mental health, behavioral problems, unintentional injuries, and poor academic performance (Adolescent Sleep Working Group, 2014). Short sleep duration during adolescence is associated with obesity (Miller, Kruisbrink, Wallace, Ji, & Cappuccio, 2018), and increases the risk of obesity in adulthood (Landhuis, Poulton, Welch, & Hancox, 2008). The National Sleep Foundation, with endorsement from the European Sleep Research Society, recommends 8 to 10 hours of sleep per 24-hour cycle (Hirshkowitz et al., 2015) as the optimal sleep duration for adolescents aged 14-17 years, and 9 to 11 hours of sleep for children aged 6-13 years. However, recent self-report data indicate the mean sleep duration among European teens aged 15-18 years is 7.97 (±1.10) and 7.84 (±1.20) hours for females and males, respectively (Ohayon, Roberts, Zulley, Smirne, & Priest, 2000). Moreover, in a Dutch cohort, approximately 20% of adolescents self-reported sleep disturbances (Verkooijen et al., 2018).

It has been suggested that physical activity, aside from its numerous health benefits, may promote longer and better sleep (Kredlow, Capozzoli, Hearon, Calkins, & Otto, 2015). Additionally, sufficient nighttime sleep may promote physical activity the following day due to increased energy (decreased daytime sleepiness) (X. Chen, Beydoun, & Wang, 2008). The association between sleep and physical activity has been found to be bi-directional in adult populations (Gabriel et al., 2017), such that optimal sleep duration results in more physical activity/less sedentary time in the subsequent day, and more physical activity during the daytime results in optimal sleep duration that night. However, results so far have been inconsistent (Baron, Reid, & Zee, 2013; Kishida & Elavsky, 2016; Lambiase, Gabriel, Kuller, & Matthews, 2013; Mitchell et al., 2016).

In adolescent populations, analyses on the bidirectional associations between sleep and physical activity have also been mixed owing primarily to differing study designs and analytic methods, and varying physical activity and sleep measures (Krietsch, Armstrong, McCrae, & Janicke, 2016; Master et al., 2019; Ortega et al., 2010; Soric et al., 2015). Additionally, these previous adolescent studies have primarily focused only on moderate-to-vigorous intensity physical activity (MVPA) rather than the range of activity intensities. This ignores the contribution of all behaviors occurring within a finite 24-hour period (sleep, sedentary time and total physical activity) on health benefit in adolescent populations (Kuzik et al., 2017; Renninger et al., 2020). Furthermore, it is important to understand the co-dependence of these behaviors (Pronk et al., 2004). Specifically, an alteration to the time spent sleeping will require the displacement of the time spent in some other waking-time, energy conserving or expending behavior, such as sedentary or physical activity behaviors (Chaput, Saunders, & Carson, 2017; Dulloo, Miles-Chan, & Montani, 2017; Tremblay, Chaput, et al., 2017). However, no existing studies that have examined the bidirectional relations of sleep and waking time physical behaviors (i.e. sedentary behavior and physical activity) in adolescent populations have accounted for the compositional nature of the data.

Therefore, the purpose of this study is to examine the bidirectional associations between short and long sleep and the accelerometer-derived proportion of time spent sedentary and physically active (as percentages of total wear-time and in relation to the other physical behaviors using a compositional data analysis approach, CoDA) among Dutch adolescents. Given the strong associations between sleep duration and the risk of obesity among adolescents, and the differing developmental stages of males and females during adolescence (Patton & Viner, 2007), we assessed the potential for confounding by age and weight status and we stratified the analyses by gender. Additionally, we used categories of sleep duration instead of sleeping time to account for different sleeping recommendations for the two age groups included in this study.

Methods

All materials and supporting documents are available at the Open Science Framework (OSF) repository at https://osf.io/5hpdb/?view_only =0de4df6f0af3462c8b31bba26a151703.

This sample was drawn from participants in the Focus on Strength (FOS) randomized trial (2014-2016). FOS examined the effects of muscle strengthening exercises on body composition among Dutch adolescents aged 11-15 years (Ten Hoor et al., 2016). Briefly, the FOS study provided strength training exercises to overweight adolescents during school-based physical education, along with motivational sessions (group and individual), to determine the effect on overall physical activity levels over a 1-year period. As part of the study protocol, participants were asked to complete daily sleep diaries while wearing an Actigraph GT3x (Actigraph, Pensacola, FL, USA) accelerometer for one week at baseline (T0) and after 12 months at follow up (T1) (Ten Hoor et al., 2016; Ten Hoor et al., 2018). In the current study, due to the reduced availability of participants having data at both timeslots, only the baseline data were considered in the analyses. Yet, we conducted all analyses of the current study also with the follow up data as sensitivity analyses (results retrievable from the OSF directory).

Nine Dutch Schools were recruited via school management. Of the 808 students who were eligible to participate, 34 students declined. Eventually, 774 adolescents (11–15 years old) participated in the study. Following consent from the schools, parents and their children were informed about the intervention and related outcome measurements and told they could refuse participation at any time. The study methods and consent procedure were approved by the Ethical Review Committee of the Faculty of Psychology and Neuroscience, Maastricht University, the Netherlands [ERCPN-05-09-2012A1]. Of the 774 FOS participants, 294 provided sleep diaries and valid accelerometer data the day before and/or after, for at least 4 days.

Data collection

The student administration of the schools provided the students' gender and date of birth. Anthropometrics were measured using standard procedures (Centers for Disease Control and Prevention (CDC)). Height (SECA 213 stadiometer, Hamburg, Germany) and weight (SECA 877 scale, Hamburg, Germany) were measured without shoes or heavy clothes to the nearest 1 mm and 0.1 kg, respectively. Body mass index (BMI) was calculated as weight/height squared (kg/m2) and Z-scores from age and sex specific reference values (Fredriks, van Buuren, Wit, & Verloove-Vanhorick, 2000). Body composition was assessed by deuterium dilution (Westerterp, Wouters, & van Marken Lichtenbelt, 1995) following the procedure proposed by Schoeller and colleagues (Schoeller et al., 1986). We calculated fat-free mass with age-specific hydration fractions (Timothy, 1989). Compared to underwater weighing, deuterium dilution is a valid method to assess fat mass percentage (van der Kooy et al., 1992; Westerterp et al., 1991).

To assess sedentary behavior and physical activity, students were asked to wear an Actigraph GT3x for five consecutive days, except during water-based activities such as swimming or taking a shower. Since the best wearing position for an accelerometer to assess daily life physical behaviors is as close to the center of mass as possible, the participants were asked to wear the Actigraph on their lower back (Plasqui, 2017; Plasqui et al., 2013; Yngve, Nilsson, Sjostrom, & Ekelund, 2003). Students were told to wear the device for at least one weekend day and, when wearing it during the week, to wear it on schooldays. The accelerometer was attached by an adjustable elastic belt. The Actilife software (Actigraph Corp. Release v6.13.3. Pensacola, FL: Actigraph LLC) was used to generate activity counts (counts per minute, CPM) and, consequently, intensity level categories (sedentary behavior, light, and MVPA). Accelerations were read at a rate of 30 Hz. We reintegrated the data with an output data rate of 15-second epochs because the determination of the CPM cut-offs for determining physical behavior levels were done with this data output rate (Banda et al., 2016; Evenson, Catellier, Gill, Ondrak, & McMurray, 2008).

The ActiLife software was used to scan the raw data for wear and non-wear times using the algorithm by Choi and colleagues considering the vertical axis counts and a minimum non-wear time window of 90-minutes (Choi, Ward, Schnelle, & Buchowski, 2012). We included data from participants who had worn the accelerometer at least 7-hours per day for a minimum of 4-days. Although higher wear-time cut-off values yield higher reliability of accelerometer data, they result in smaller analyzable sample sizes (Toftager et al., 2013). Therefore, we conducted a separate analysis to determine the highest possible wear-time cut-offs while keeping a maximum of analyzable data points (number of days). Thereby, we created datasets with all possible cut-off values and conducted Wilcoxon-Sign-Ranked tests to test for significant differences of participant characteristics (i.e., age, gender, BMIz score, sleep duration, activity as percentage per wearing day) of those new datasets compared to characteristics of the minimum cut-off of 0 days and 0 hours (see OSF repository). This resulted in establishing 7-hours per day for a minimum of 4 days cut-off as valid, with an estimated reliability of approximately 0.70 (Spearman-Brown coefficient) in adolescents of this age group (Trost, Pate, Freedson, Sallis, & Taylor, 2000).

Total daily accelerometer counts were estimated using the amount of daily counts detected by the vertical axis during wear periods. Daily proportions spent in different intensity levels was calculated using the cut-off points proposed by Evenson and colleagues (Evenson et al., 2008; Trost, Loprinzi, Moore, & Pfeiffer, 2011). Descriptive analyses were performed for both daily time in different intensity levels and proportion of wear-time (%). To account for the effect of the time spent wearing the device on physical activity occurring during waking hours, we analyzed the data as proportions of the day spent in each behavior in the multivariable models. This was done by using both proportions in relation to the daily wearing time and by using proportions in relation to the other two behaviors, which was done by using a CoDA approach (Chastin, Palarea-Albaladejo, et al., 2015).

Sleep actigraphy data were not collected in this sample due to perceived discomfort from the waist-worn Actigraph during sleep. However, on days that the accelerometer was worn, participants completed sleep and accelerometer wear-time diaries indicating times of the day when they woke up and went to bed, and any other time they put on and took off the accelerometer. The reported clock times in and out of bed were used to estimate sleep duration (minutes per night) (Gabriel et al., 2017; Lambiase et al., 2013). Reported time in bed from sleep diaries has been shown to be comparable to objective sleep duration measurements (Lockley, Skene, & Arendt, 1999; McCrae et al., 2005; Monk et al., 1994). Categories of sleep duration were used for the mixed-effects models because of differing recommendations per age group (8-10 hours for 14-17 years; 9-11 hours for 9-13.9 years) and because of the fact that sleep diaries are based on self-reports which cannot measure time-in-bed to minutes precision (Hirshkowitz et al., 2015). Short and long sleep were defined as being shorter and longer than the age-specific optimal recommended sleep duration.

Statistical analyses

To analyze the bidirectional association of sleep categories and physical activity, two long format datasets were created with each row representing one day per subject. In the first dataset, nighttime sleep duration was combined with the physical behavior that proceeded it in time to examine the association of sleep (i.e. predictor) and the following day's physical behaviors (i.e. outcome). In the second dataset, physical behaviors during waking-hours were combined with the proceeding night's sleep duration to examine the association of physical activity (i.e. predictor) and the succeeding night's sleep (i.e. outcome).

We performed descriptive univariate analyses and assessed data normality using histograms and QQ plots. Non-normally distributed variables were reported as medians and Inter-Quartile-Ranges (IQR), normally distributed variables were reported as means and standard deviations (SD). Sedentary behavior, light physical activity, and MVPA were presented with compositional geometric means and log-ratio variance, which are "the variances of the logarithms of all pair-wise ratios between parts" (Chastin, Palarea-Albaladejo, et al., 2015). We reported categorical variables as absolute numbers and percentages. To assess presumed differences by days of the week in, i) physical activity levels, ii) times in and out of bed, and iii) sleep durations, we performed descriptive analyses stratified by day of the week (e.g. Monday).

To examine the association between sleep duration and physical behavior levels the next day, we used linear mixed-effects model with repeated measures and random intercepts on the individual level, since, for most of the models, random intercept models showed better fit compared to fixed intercept models when applying the Akaike information criterion (Akaike, 1974), and we were interested in the day-to-day associations within participants. Since the measurements were auto-correlated we used an autoregressive covariance structure (see other linear models and overviews of auto-correlations in the OSF directory). To examine the association between daytime physical behavior and sleep categories (e.g. short sleep, optimal sleep, and long sleep), we used generalized linear mixed-effects models with repeated measures, random intercepts on the individual level and a binomial distribution (e.g., optimal sleep vs. long sleep) to estimate the sleep categories, with the optimal sleep duration as the reference category.

Instead of using overall activity times, we only analyzed proportions of the day (waking-hours) spent in sedentary behavior, light activity, and MVPA because shorter days resulted in less available time for these physical behaviors. Additionally, physical behaviors were operationalized using the CoDA approach to account for interdependence and multicollinearity of all three activity levels (i.e. less sedentary behavior proportion results in more light activity) (Chastin, Palarea-Albaladejo, et al., 2015). Firstly, the durations of the three activity levels were transformed into proportions of the time that the accelerometer was worn on a specific day. Secondly, the data were transformed by isometric log-ratio transformations (e.g. sedentary behavior proportion) and adjusted for the proportion of the day spent in the other two behaviors (e.g. light physical activity and MVPA), e.g. $zSB = \sqrt{\frac{2}{3}} \ln \frac{SB}{\sqrt{LIPA\ x\ MVPA}}$ (Chastin, Palarea-Albaladejo, et al., 2015). Each of the three physical behaviors (e.g. sedentary behavior) was once on the first position, with a second variable (e.g. $zLIPA = \sqrt{\frac{1}{2}} \ln \frac{LIPA}{MVPA}$) on the second position, providing information on the entire physical behavior composition. The variable that was on the first position in the composition was used to interpret its coefficient (physical behavior composition as predictor), and as outcome variable (physical behavior composition as outcome) (Rasmussen et al., 2018). It provided information on the relative importance of this first part in relation to the other two parts. We did not incorporate the binary outcome of meeting the aerobic physical activity recommendations since the MVPA guidelines (at least 60-minutes per day) were only met in 33 of the 1620 recorded days, across participants.

All tests for statistical significance were two-sided, with an alpha of .05. Data analyses were performed using R version 3.4.1. Sensitivity analyses of the datasets without outliers (detected with the Mahalanobis distance (Mahalanobis, 1936)) and from the follow-up assessment at 1-year post baseline (T1) were conducted, and the results can be found in the OSF directory. Covariates were selected using backwards elimination where a predictor was retained if the p-value was less than 0.20. All analyses were controlled for age (locked in the models). For sleep categories predicting physical activity, we ran the analyses separately by gender.

Results

Of the 774 participants, 598 (77.3%) wore the accelerometer and 427 (71.4%) displayed at least 4-days of at least 7-hours of wear-time, of which 306 (71.7%) returned valid sleep diaries. We further excluded 12 (3.9%) participants who had missing personal data such as gender or body mass information. This resulted in an analytical sample of 294 (162 females, 132 males) adolescents with a mean age of 12.8 (interquartile range [IQR] = 0.7) years, a median BMIz score of 0.2 (IQR = 1.2) kg/m^2, and a median fat mass of 25.4 (IQR = 7.8) % (Table 1). The known anthropometric characteristics of the original sample did not differ significantly from the sample being analyzed in this study (see OSF directory). General information about the participant characteristics can be retrieved from the FOS effect paper (Ten Hoor et al., 2018).

In the dataset of sleep estimating physical behavior the next day, participants' median reported times in bed were consistently between 21:30

and 21:45 across weekdays and between 23:00 and 23:01 on weekends. Participants' median reported times out of bed were between 07:00 and 07:15 during the weekdays, and between 09:00 and 09:30 during weekends. On weekends, participants reported longer sleep durations and shorter accelerometer wear-times compared to weekdays. This added up to similar amounts of data on a 24-hour day (see supplementary files). Physical behavior proportions were consistent across the week except on Wednesdays and Thursdays where participants seemed to accumulate more MVPA, and on Sundays, where they seemed to accumulate less MVPA (Figure 1). In the dataset of physical behavior estimating subsequent sleep duration, results were similar (data not shown, but can be found in the OSF directory).

Sleep category predicting sedentary behavior and physical activity the next day

The results of the linear mixed-effects models with repeated measures for sleep category estimating physical activity and sedentary behavior are depicted in Table 2. Among female adolescents, long sleep was associated with a significantly smaller proportion of waking-minutes sedentary the following day (-3.02%, SE = 1.05, p < .01, 95% CI [-5.09, -0.96]) and a significantly greater proportion of waking-minutes in MVPA the following day (1.69%, SE = 0.48, p < .001, 95% CI [0.75, 2.64]). Among male adolescents, short sleep was associated with a significantly smaller proportion of waking-minutes the following day spent in sedentary behaviors (-2.57%, SE = 1.21, p = .03, 95% CI [-4.95, -0.19]) and a significantly greater proportion of waking-minutes the following day spent in light physical activity (1.96%, SE = 0.86, p = .02, 95% CI [0.27, 3.65]), compared to those with optimal sleep.

Results from the CoDA models were similar for females. CoDA models indicated that long sleep was significantly negatively associated with the proportion of time spent in sedentary behavior compared to light activity and MVPA (-0.15, SE = 0.06, p < .01, 95% CI [-0.26, -0.04]), and with the proportion of time spent in MVPA compared to sedentary behavior and light activity (0.18, *SE* = 0.07, *p* = .01, 95% CI [0.04, 0.32]; see Figure 2a). Similar associations were not found among males in the CoDA models (see Figure 2b).

Table 1. Descriptive characteristics of participants 2014-2015.

	Female	Male	Total
	n=162	n=132	n=294
Age, mean (SD)	12.8 (0.7)	12.9 (0.6)	12.8 (0.7)
Sleep[a]			
Time to bed (hh:mm), median (IQR)	22:14 (00:56)	22:08 (00:52)	22:10 (00:55)
Time out of bed (hh:mm), median (IQR)	08:06 (00:40)	08:05 (00:54)	08:06 (00:47)
Sleep duration (min d^{-1}), median (IQR)	594.4 (50.9)	596.2 (65.9)	595.0 (55.9)
Short sleeper, n (%)	16 (9.9)	13 (9.8)	29 (9.9)
Long sleeper, n (%)	12 (7.4)	7 (5.3)	19 (6.5)
Optimal sleeper, n (%)	134 (82.7)	112 (84.8)	246 (83.7)
Physical activity [b]			
Wear time (min d^{-1}), median (IQR)	694.0 (157.2)	712.5 (198.4)	701.2 (181.1)
Sedentary portion[c] (% d^{-1}), mean (SD)	72.6 (6.4)	72.2 (6.0)	72.4 (6.2)
Sedentary compositional geom. mean, log ratio variance sit-light, sit-MVPA	73.6 (0.1,0.3)	73.2 (0.1, 0.3)	73.4 (0.1, 0.3)
Light portion[c] (% d^{-1}), mean (SD)	22.8 (4.9)	22.6 (4.6)	22.7 (4.7)
Light compositional geom. mean, log ratio variance light-sit, light-MVPA	22.9 (0.1, 0.2)	22.8 (0.1, 0.1)	22.8 (0.1, 0.2)
MVPA portion[c] (% d^{-1}), median (IQR)	3.9 (2.6)	4.7 (2.9)	4.3 (3.0)
MVPA activity compositional geom mean, log ratio variance MVPA-light, MVPA-sit	3.5 (0.2, 0.3)	4.0 (0.1, 0.3)	3.7 (0.2, 0.3)
Meeting guidelines (% d^{-1}), median (IQR)	0 (0.2)	0 (0.3)	0 (0.2)
Anthropometrics			
BMIz score	0.3 (1.2)	0.1 (1.2)	0.2 (1.2)
Fat mass (%)	27.0 (7.3)	23.1 (7.9)	25.4 (7.8)
Underweight, n (%)	4 (2.5)	2 (1.5)	6 (2.0)
Normal weight, n (%)	115 (71.0)	101 (76.5)	216 (73.5)
Overweight, n (%)	31 (19.1)	19 (14.4)	50 (17.0)
Obese, n (%)	12 (7.4)	10 (7.6)	22 (7.5)

Abbreviations: SD, standard deviation; hh:mm, hours:minutes; IQR, interquartile range; min d^{-1}, minutes per day; % d-1, proportion of the day; ct d^{-1}, counts per day; MVPA, moderate-to-vigorous intensity physical activity.

[a] Reported time in bed at night and the time out of bed the following morning were used to estimate the total time in bed. Short sleep defined as those nights with <8/9 hours reported time in bed. Long sleep defined as those nights with >10/11 hours reported time in bed. Optimal sleep is defined as those nights with 8-10/9-11 hours reported time in bed.

[b] Estimates of sedentary and physical activity behaviors are estimated via accelerometry. Sedentary intensity defined as 0-100 counts. Light intensity defined as 101-2295 counts. Accumulated MVPA defined as ≥2296 counts. Meeting guidelines defined as the proportion of days accumulating at least 60-minutes of MVPA.

[c] The percent of the day is the estimated proportion of waking-minutes spent in each activity level.

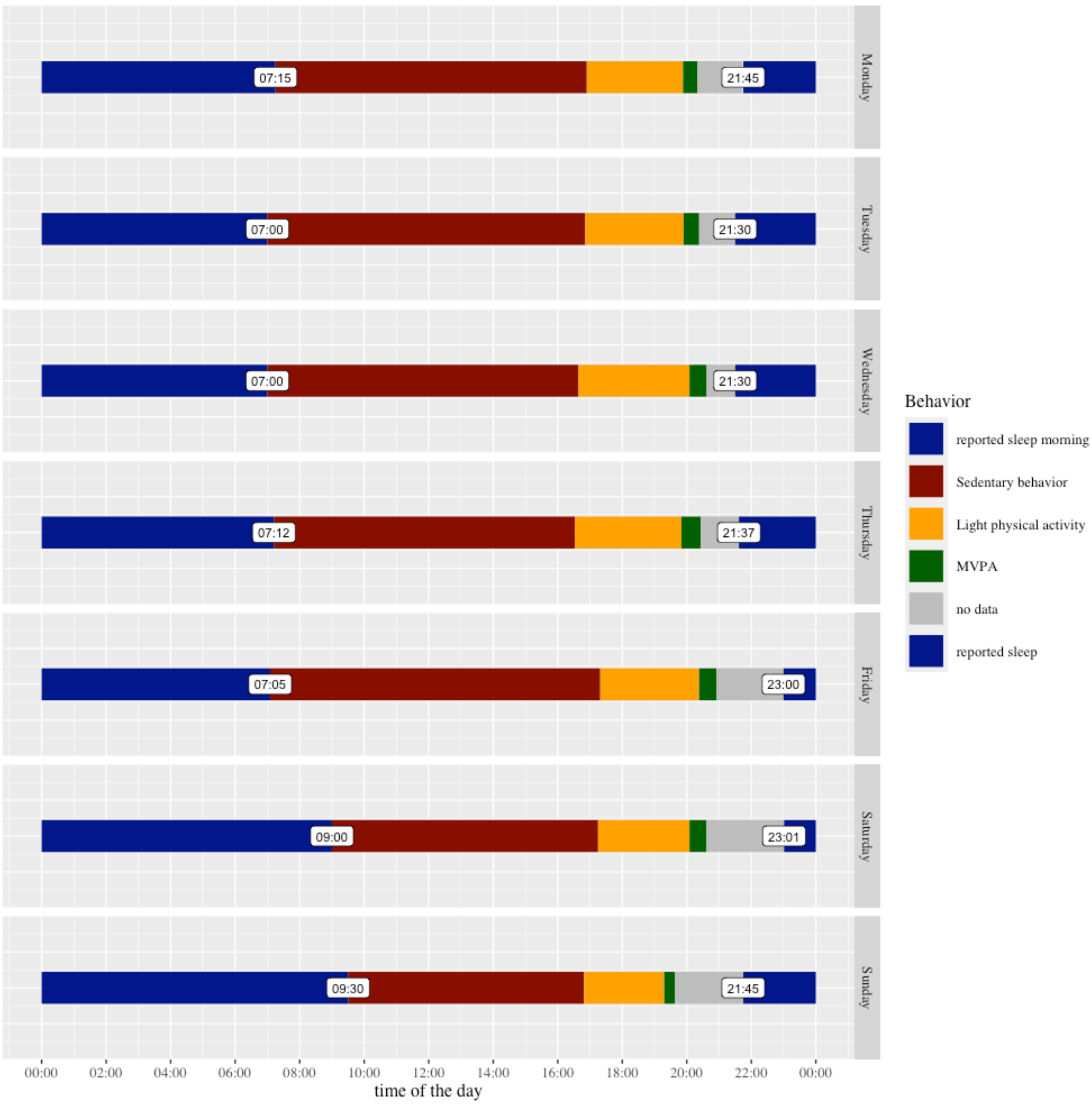

Figure 1. Daily summary estimates reflecting reported time in bed predicting PA and sedentary behavior the next day (Sleep-PA)

Physical activity and sedentary behavior predicting sleep duration that night

The generalized linear mixed-effects models with repeated measures to determine the association between daytime physical activity and nighttime sleep are presented in Table 3. Neither the results of the CoDA analyses nor the results of the analyses using physical activity portions revealed significant effects.

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Table 2. Linear mixed-effects models with repeated measures for sleep category predicting physical activity and sedentary behavior the following day.

Sleep duration[a]	Sedentary behavior				Light physical activity				MVPA			
	β	*SE*	*p*	95% CI	β	*SE*	*p*	95% CI	β	*SE*	*p*	95% CI
Physical activity portions (% d^{-1})[b]												
Females (number of obs.: 427, *n* = 104)												
Short sleep	-0.28	0.99	.78	-2.23, 1.68	0.37	0.77	.63	-1.15, 1.88	-0.12	0.45	.79	-0.99, 0.76
Long sleep	-3.02	1.05	< .01	-5.09, -0.96	1.25	0.81	.12	-0.34, 2.84	1.69	0.48	< .001	0.75, 2.64
Intercept	57.08	15.62	< .001	26.35, 87.81	34.97	12.36	< .01	10.65, 59.28	7.99	5.38	.14	-2.58, 18.57
Males (number of obs.: 345, *n* = 83)												
Short sleep	-2.57	1.21	.03	-4.95, -0.19	1.96	0.86	.02	0.27, 3.65	0.60	0.55	.28	-0.48, 1.67
Long sleep	0.93	1.32	.48	-1.66, 3.53	-0.38	0.94	.69	-2.23, 1.47	-0.54	0.59	.36	-1.71, 0.62
Intercept	77.60	15.42	< .001	47.23, 107.97	19.30	11.73	.10	-3.80, 42.39	3.11	6.04	.61	-8.77, 15.00
Compositional data analysis												
Females (number of obs.: 427, *n* = 104)												
Short sleep	-0.01	0.05	.83	-0.12, 0.09	0.03	0.03	.42	-0.04, 0.10	-0.02	0.07	.77	-0. 16, 0.11
Long sleep	-0.15	0.06	< .01	-0.26, -0.04	-0.03	0.04	.46	-0.10, 0.04	0.18	0.07	.01	0.04, 0.32
Intercept	0.81	0.76	.29	-0.68, 2.31	0.30	0.45	.51	-0.59, 1.19	-1.12	0.87	.20	-2.83, 0.59
Males (number of obs.: 345, *n* = 83)												
Short sleep	-0.11	0.07	.10	-0.25, 0.02	0.03	0.04	.45	-0.05, 0.11	0.09	0.09	.33	-0.09, 0.26
Long sleep	0.09	0.07	.23	-0.06, 0.23	0.02	0.04	.71	-0.07, 0.10	-0.12	0.09	.20	-0.31, 0.06
Intercept	2.02	0.83	.02	0.38, 3.65	0.40	0.43	.35	-0.44, 1.24	-2.39	0.95	.01	-4.27, -0.51

Abbreviations: % d^{-1}, proportion of the day; CI, confidence interval; MVPA, moderate-to-vigorous intensity physical activity; SE, standard error.

[a]Reported time in bed at night and the time out of bed the following morning were used to estimate the total time in bed. Short sleep defined as those nights with <8/9 hours reported time in bed. Long sleep defined as those nights with >10/11 hours reported time in bed. The referent group is defined as those nights with 8-10/9-11 hours reported time in bed.

[b] Estimates of sedentary and physical activity behaviors are estimated via accelerometry. Sedentary intensity defined as 0-100 counts. Light intensity defined as 101-2295 counts. Accumulated MVPA defined as ≥2296 counts.

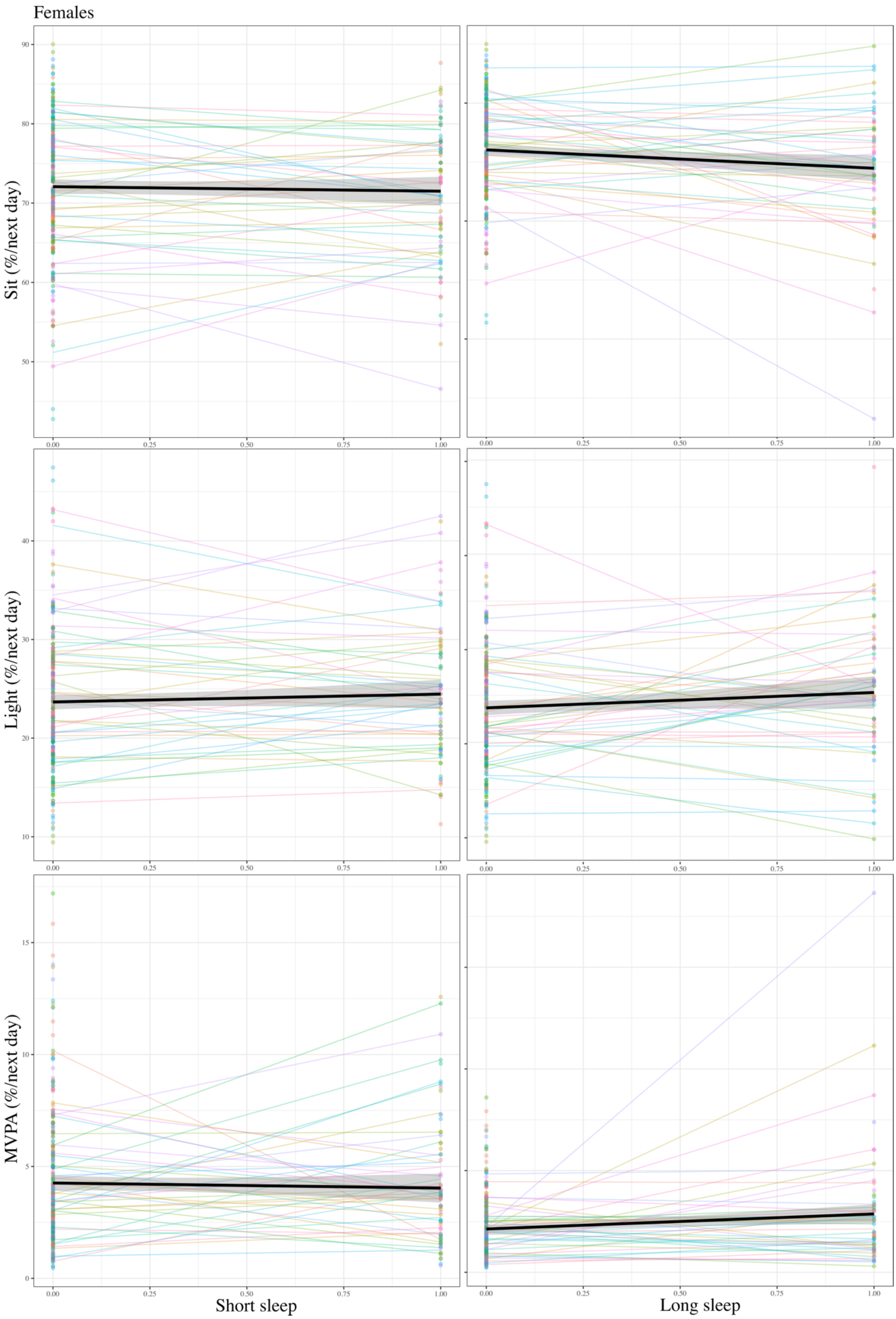

Figure 2a. Model-predicted influence of short and long sleep on the portion of physical activity the next day among females: Spaghetti plot of average (thick) and subject specific (thin) regression lines.

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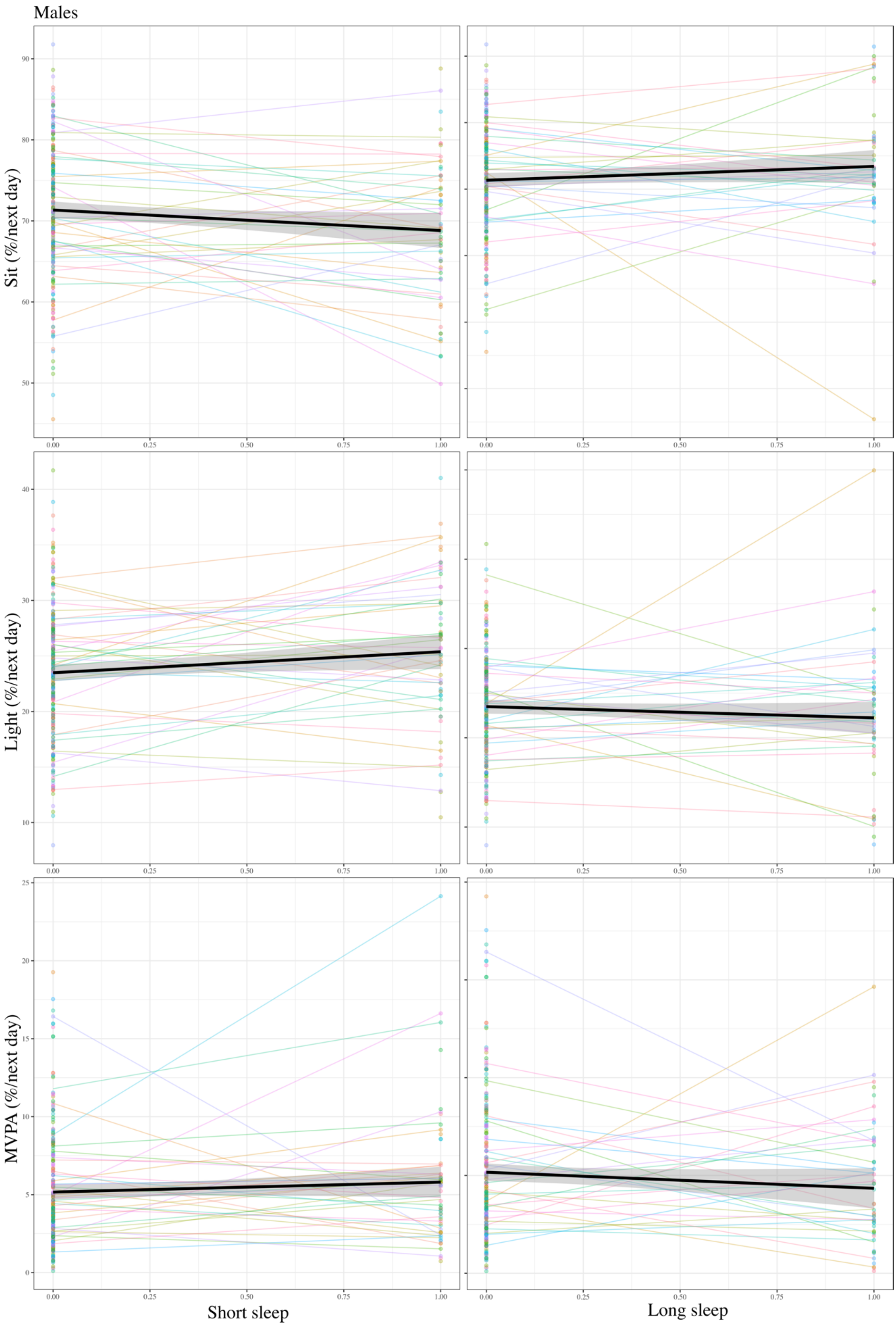

Figure 2b. Model-predicted influence of short and long sleep on the portion of physical activity the next day among males: Spaghetti plot of average (thick) and subject specific (thin) regression lines.

Table 3. Generalized linear mixed-effects models with repeated measures for physical activity and sedentary behaviors predicting sleep category that night.

	Short sleep[b]				Long sleep[b]			
Physical activity [a]	β	*SE*	*p*	95% CI	β	*SE*	*p*	95% CI
Females (number of obs.: 475, *n* = 116)								
Physical activity portions								
Sedentary portion, % d^{-1}	-0.00	0.02	.99	-0.04, 0.04	-0.01	0.02	.52	-0.04, 0.02
Intercept	-10.72	4.54	.02	-20.17, -1.92	-2.62	3.90	.50	-10.44, 5.18
Light portion, % d^{-1}	0.02	0.02	.42	-0.03, 0.07	0.00	0.02	.93	-0.04, 0.05
Intercept	-11.32	4.41	.01	-20.51, -2.74	-3.53	3. 70	.34	-10.94, 3.89
MVPA portion, % d^{-1}	-0.07	0.05	.16	-0.18, 0.02	0.05	0.04	.19	-0.03, 0.12
Intercept	-10.70	4.41	.02	-19.88, -2.11	-3.45	0.04	.35	-10.89, 3.99
Compositional data analysis								
Sedentary behavior	-0.41	0.49	.40	-1.39, 0.56	-0.03	0.47	.95	-0.94, 0.90
Light physical activity	0.92	0.63	.14	-0.30, 2.19	-0.36	0.59	.55	-1.56, 0.80
MVPA	-0.51	0.31	.10	-1.14, 0.09	0.39	0.30	.20	-0.19, 0.99
Intercept	-11.44	4.43	< .01	-20.67, -2.86	-2.67	3.80	.48	-10.26, 4.98
Males (number of obs.: 369, *n* = 88)								
Physical activity portions								
Sedentary portion, % d^{-1}	0.00	0.02	.86	-0.04, 0.05	0.04	0.02	.07	-0.00, 0.09
Intercept	-14.87	5.03	< .01	-25.79, -5.43	-7.99	6.23	.20	-20.88, 4.65
Light portion, % d^{-1}	-0.01	0.03	.81	-0.07, 0.05	-0.06	0.03	.07	-0.13, 0.00
Intercept	-14.48	4.77	< .01	-24.77, -5.38	-3.51	0.03	.56	-15.92, 8.89
MVPA portion, % d^{-1}	0.00	0.04	.99	-0.09, 0.08	-0.06	0.06	.25	-0.18, 0.04
Intercept	-14.59	4.74	< .01	-24.83, -5.57	-4.44	6.03	.46	-16.90, 7.93
Compositional data analysis								
Sedentary behavior	0.18	0.56	.75	-0.91, 1.29	1.15	0.62	.06	-0.07, 2.41
Light physical activity	-0.43	0.71	.55	-1.83, 0.98	-0.88	0.79	.27	-2.46, 0.70
MVPA	0.25	0.34	.47	-0.42, 0.93	-0.27	0.38	.48	-1.04, 0.47
Intercept	-14.48	4.79	< .01	-14.87, -5.42	-6.42	6.04	.29	-18.94, 5.89

Abbreviations: % d^{-1}, proportion of the day; CI, confidence interval; MVPA, moderate-to-vigorous intensity physical activity; SE, standard error.

[a]Estimates of sedentary and physical activity behaviors are estimated via accelerometry. Sedentary intensity defined as 0-100 counts. Light intensity defined as 101-2295 counts. Accumulated MVPA defined as ≥2296 counts.

[b]Reported time in bed at night and the time out of bed the following morning were used to estimate the total time in bed. Short sleep defined as those nights with <8/9 hours reported time in bed. Long sleep defined as those nights with >10/11 hours reported time in bed. The referent group is defined as those nights with 8-10/9-11 hours reported time in bed.

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Discussion

This study examined the associations between daytime physical behaviors with categories of sleep duration the following night, and nighttime sleep with the following day's physical behaviors. Results from the first research question indicate that nighttime sleep was partially related to the following day's physical behaviors among this cohort of Dutch adolescents. Among females, long nighttime sleep was significantly associated with more time spent in the following day's health-benefiting MVPA and less time spent in sedentary behavior. Short sleep was not associated with next days' physical behaviors among females. These associations were found both with the proportions and with the CoDA analyses. For males, short nighttime sleep was associated with a smaller and higher proportion of time the following spent sedentary and in light-intensity activities, respectively. However, this association was only found when applying proportions not when applying CoDA analyses. The reason is that sedentary behavior was only replaced by light activity and not by both light activity and MVPA which would have yielded more equal distributions of the three behaviors and, therefore, lower sedentary behavior and higher light activity CoDA values. Long sleep was not associated with next days' physical behaviors among males. There were no significant findings when estimating the association between daytime physical behavior and the following night's sleep.

Previous studies on the association of sleep and physical activity among adolescents have found the strongest and most consistent associations between nighttime sleep and the following day's physical behaviors (Krietsch et al., 2016; Master et al., 2019; Ortega et al., 2010; Soric et al., 2015). However, the results are mixed. Ortega et al. (2010) found that males that reported a shorter sleep duration had lower odds of engaging in any intensity of physical activity the following day (Ortega et al., 2010). Similarly, Master et al. (2019) found significant associations with sleep duration and MVPA, however in different directions. They found that a longer sleep duration, rather than a shorter sleep duration, resulted in less MVPA the following day (Master et al., 2019). Whereas, Soric et al. (2015) and Krietsch et al. (2016) found that total sleep time was unrelated to the following day's MVPA, but more time in bed and sleep onset (the timing of when the subject went to bed), respectively, were significantly associated with the following day's MVPA (Krietsch et al., 2016; Soric et al., 2015). Previous studies' associations are most consistently statistically significant when investigating relationships within subjects (across multiple days), however these studies did not account for the compositional nature of the 24-hour activity data. In addition, other discrepancies in results could be attributed to a number of factors, including the varying methods to measure physical behaviors and sleep (Soric et al., 2015), and differing analytic methods to control for the potentially confounding effects of gender and age. Of the other studies on the bidirectional associations between sleep and physical behaviors among adolescents (Krietsch et al., 2016; Master et al., 2019; Ortega et al., 2010; Soric et al., 2015), only Soric et al. and Ortega et al. analyzed the data within gender strata. Soric et al. found that the lower estimated total daily energy expenditure resulting from a longer sleep duration differed between genders. Ortega et al. found that in both males and females, morning tiredness (but not necessarily sleep time) was associated with significantly lower odds of leisure-time physical activity the following day. Further, short sleep duration was associated with the time spent watching television in males, but not females. Given these findings, and the current study's differing findings by gender, indicates the importance of stratified analyses by gender on this topic in future research. However, taking the collective findings from this and previous studies, among adolescent populations, there seems to be no consistent support for associations between nighttime sleep and the following day's physical behavior in adolescents.

Interestingly, in a previous study among adults, longer nighttime sleep was associated with less sedentary behavior, and shorter nighttime sleep was associated with more light-intensity physical activity (Gabriel et al., 2017). This closely aligns with the current study's findings for females (longer nighttime sleep was associated with less sedentary behavior), and males (shorter nighttime sleep was associated with more light-intensity physical activity), respectively. As the previous study's authors noted, this may indicate that physical activity levels are more dependent upon the time available in the day, which is the direct result of the time spent sleeping. However, the data in this previous study were not analyzed as the total proportion of the data, but rather as an estimate of total minutes (Gabriel et al., 2017), while in the current study, proportions of the days as well as a compositional data approach were used. Therefore, the findings may be due to other external forces, such as fixed schedules or parental/school schedules, which was confirmed by the fact that females were more active and less sedentary on weekends, while males were more active and less sedentary during the week (especially on Tuesdays and Wednesdays; see descriptive data in the OSF directory). However, the allocation of time spent physically active being dependent upon external forces among adolescents may be explored further using randomized trials which control for planned versus unplanned physical activity.

The strengths of this study include the use of accelerometry among a highly compliant cohort of adolescents. Aside from removing self-reporting error with this device-based assessment of physical behavior, accelerometry also detects movement and non-movement across the full spectrum of intensities, including sedentary and light-intensity physical activity. This allowed the evaluation of sleep as it relates to activities beyond MVPA, to encompass the full 24-hour activity cycle. This represents a paradigm shift in the field towards an integrated model that incorporates both sleep and waking behaviors to optimize health, rather than focusing on a single behavior (Rosenberger et al., 2018). Despite these strengths, this study has limitations that should be noted. First, the generalizability of these results is limited by the sample's homogenous characteristics (age, race/ethnicity, socioeconomic status). However, the results of this study generally align with other studies' findings and the homogenous sample provides increased internal validity in light of the relatively small sample size. Second, although actigraphy measured waking behaviors, it did not measure sleep duration, but rather, we relied upon a proxy estimate based on self-reported time to bed and time out of bed. However, self-reported time in/out of bed from sleep diaries has been shown to be comparable to objective sleep duration measurements (Lockley et al., 1999; McCrae et al., 2005; Monk et al., 1994). We were able to confirm in additional analyses (not reported, but retrievable in the OSF directory) the reported times in bed and time spent in waking behaviors generally summed to a full day. Additionally, results from previous studies using sleep actigraphy among adolescents (Master et al., 2019) generally align with the current study's findings.

These findings provide an important addition to the literature aiming to understand the possible bidirectional associations of sleep and physical activity among children and adolescents. Adolescents undergo significant developmental changes that are known to impact these important health behaviors, and socially, are subject to non-discretionary activities that may impact their time spent in health promoting or compromising behaviors. Furthermore, the impact of daytime schedules on physical activity and nighttime sleep metrics (e.g., sleep duration, sleep quality, sleep onset, sleep latency) should be considered. This will allow us to understand if physical activity impacts sleep in ways that may not appear by measuring the time in bed. Other confounding factors such as pubertal status, socio-economic status, and school start times might be worth considering in future research and with more available data. Although experimental designs will allow for the causal relations between these behaviors to be explored and will provide for greater variability in the variables of interest, the feasibility of such designs is questionable. Therefore, future research may strive to take advantage of natural experimental designs. Overall, these results suggest that promoting best sleep practices (Hirshkowitz et al., 2015) may have a positive impact on daytime physical activity behaviors.

CHAPTER 5

Sequential activity Patterns and Outcome-specific, Real-time and Target group-specific feedback: the SPORT algorithm

Berninger, N. M., ten Hoor, G. A., Plasqui, G., & Crutzen, R. (2020). Sequential activity Patterns and Outcome-specific, Real-time and Target group-specific feedback: the SPORT algorithm. (Submitted for publication)

Abstract

Objectives. Physical activity (PA) is crucial for health but guidelines insufficiently consider PA patterns. The purpose of this study was to incorporate sequential PA patterns into one value. We validated the resulting two algorithms ($SPORT_{constant}$ and $SPORT_{linear}$) by comparing their predictive power with a compositional data approach (CoDA).

Methods. To measure PA, 397 (218 females) adolescents with a mean age of 12.4 (SD = 0.6) years wore an Actigraph on their lower back for one week. The SPORT algorithm is based on a running value, each day starting with 0 and minutely adapting depending on the behavior being performed. We used linear regression models with a behavior-dependent constant ($SPORT_{constant}$) and a function of time-in-bout ($SPORT_{linear}$) as predictors and BMI *z*-scores (BMIz) and fat mass (%FM) as exemplary outcomes.

Results. After 5-fold cross-validation, the CoDA and the $SPORT_{constant}$ models explained low variance in BMIz (2% and 1%), and low-to-moderate variance in %FM (both 5%). The variance being explained by the $SPORT_{linear}$ models was 6% (BMIz) and 9% (%FM), which was significantly better than the CoDA models ($p < .001$) according to likelihood ratio tests.

Conclusions. $SPORT_{linear}$ better predicted the health outcomes than CoDA. It enables the provision of recommendations on PA patterns. Future research should apply the new algorithm in other target groups and with other health outcomes.

Introduction

Physical inactivity during adolescence has been associated with obesity (Rauner, Mess, & Woll, 2013; Ten Hoor et al., 2018), and children and adolescents aged 5 to 17 are recommended to achieve a daily minimum of 60 minutes of moderate-to-vigorous physical activity (MVPA) (World Health Organization, 2010). Yet, 60 minutes of MVPA fill only 5-10% of the waking day, whilst the remainder is composed of sedentary behavior (SB) and light physical activity (LIPA). For example, European adolescents spend on average 9 hours of their day in sedentary behaviors (Ruiz et al., 2011). Hence, it is not surprising that, independently of an individual's MVPA, SB was found to be associated with multiple harmful health indicators, such as unfavorable body composition and higher cardio-metabolic risk (Carson et al., 2016).

The findings regarding the causal association between SB and obesity are inconsistent (Biddle, Bengoechea, & Wiesner, 2017; Ekelund et al., 2012; Kuzik et al., 2017). One of the reasons might be the different ways of operationalizing SB (Kang & Rowe, 2015). Some stressed that SB is not merely the sitting time, but the sitting pattern such as the average length of sitting bouts (Carson et al., 2016). Accumulating shorter sitting bouts and more sitting interruptions was found to have beneficial associations with cardio-metabolic outcomes (Bailey, Charman, Ploetz, Savory, & Kerr, 2017; Werneck et al., 2019). Still, it is questionable whether a single SB pattern parameter suffices to predict health, because physical activity and sedentary behavior are co-dependent and should not be considered as distinct concepts (Chastin, Palarea-Albaladejo, et al., 2015). Therefore, the reasons for the discrepancy when predicting obesity with SB might rather root in the ways of operationalizing SB and physical activity than in a lack of a relationship between SB and obesity.

Merging the idea of considering all physical behaviors as well as their patterns, it might be necessary to consider daily sequential patterns of all physical behaviors. Identical bouts of physical behaviors yet altered daily sequential orders (see Figure 1), might yield different effects on health outcomes. A SB bout S_2 following a short sitting interruption M_1 (as in day A)

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might need to be interrupted earlier than a SB bout that succeeds an hour of activity (as in day B). Due to a short-term elevation of the resting metabolic rate in response to physical activity, behaviors being performed after the physically active session show a more beneficial energy balance (Speakman & Selman, 2003). Therefore, a SB minute will have a different impact on health when following another SB minute than when following a physical activity minute. The consideration of sequential activity patterns might provide more accurate health predictions and recommendations.

The WHO's guideline applies for "all children [...] irrespective of gender, race, ethnicity [...]" (World Health Organization, 2010), but guidelines should be target group- and outcome-specific (Y. Kim, Welk, Braun, & Kang, 2015; Oja, Bull, Fogelholm, & Martin, 2010). The WHO's guideline recommends a minimum of MVPA to satisfy all individuals and all health outcomes. Yet, guidelines, which eventually will be used by individuals to set goals, should sufficiently diverge to relate to those health outcomes that are relevant to the individuals and that are challenging but realistic to achieve (Latham & Locke, 2007; Ruiz et al., 2011). Second, this guideline does not consider other physical behaviors. A person might be unable to perform MVPA but able to interrupt SB with LIPA bouts. This might be sufficiently beneficial for relevant health outcomes (Duvivier et al., 2013; Duvivier et al., 2017).

In this paper, we introduce two algorithms, which might be able to take the complexity of physical behavior into account: SPORT (*S*equence, *P*attern, *O*utcome-specific, *R*eal-time, *T*arget group-specific). The SPORT algorithms calculate scores representing sequential physical activity patterns. Resulting values can be used to provide specific populations with clear recommendations and real-time feedback in relation to specific health outcomes. This feedback can be tailored to current physical behavior patterns and is different depending on the relevant health outcome. In other words, an individual that needs to reduce their body fat might get different recommendations, compared to an individual that needs to relief their back pain (*O*utcome-specific), which is again different for a 20-year old and a 50-year old individual (*T*arget group-specific). In addition, an individual having started the day with a walk will get different recommendations compared to an individual having started the day with SB (*S*equence, *R*eal-time). Therefore, the first individual (started with walking) will have a maximum recommended sitting bout length which is longer compared to the maximum recommended sitting bout length of the second individual (started with sitting, *P*attern).

Chastin and colleagues already stressed the importance to not only use one physical behavior as predictor for health, but to include all physical behaviors of the day (i.e. SB, LIPA, MVPA, and sleep) in statistical models (Chastin, Palarea-Albaladejo, et al., 2015). Yet, incorporating also the sequential patterns of all physical behaviors in a numerical value is needed both in interventions and in research, because additional information about sequential patterns will facilitate real-time and individualized feedback and it will increase predictive utility of physical behavior. Others already succeeded to represent physical behavior patterns in visual items using colored time bars, where colors represent physical behavior categories, and, at first glance, healthy patterns can be distinguished from unhealthy patterns (Loudon & Granat, 2015). Time dependent numeric values might therefore be a solution. However, to incorporate the sequence of behaviors, each value should include a memory of the behaviors being performed before. We introduce the idea of a running-value, which accumulatively changes each minute (see Figure 1). The amount and direction of change will depend on the behavior being performed in this particular minute (e.g., when walking, the running value recovers by a points per minute). The recommended length of a sitting bout will then depend on the average of all running-values collected on that day.

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We demonstrate the development of two SPORT algorithms that incorporate sequential physical behavior patterns into one value. We use a Dutch adolescent population and their body mass index *z*-scores (BMIz) (with objectively measured height and weight, and adjusted for gender and age based on National reference values (Fredriks et al., 2000)) as well as fat mass percentages (%FM; using the valid and objective deuterium dilution procedure (Westerterp et al., 1995)) as illustrative health outcomes to validate the resulting values and to compare the predictive power with a compositional data approach (CoDA) (Chastin, Palarea-Albaladejo, et al., 2015). We hypothesize that the SPORT algorithms are able to predict both BMIz and %FM with higher accuracy compared to the CoDA approach because SPORT contains additional information on the daily sequence of the behaviors.

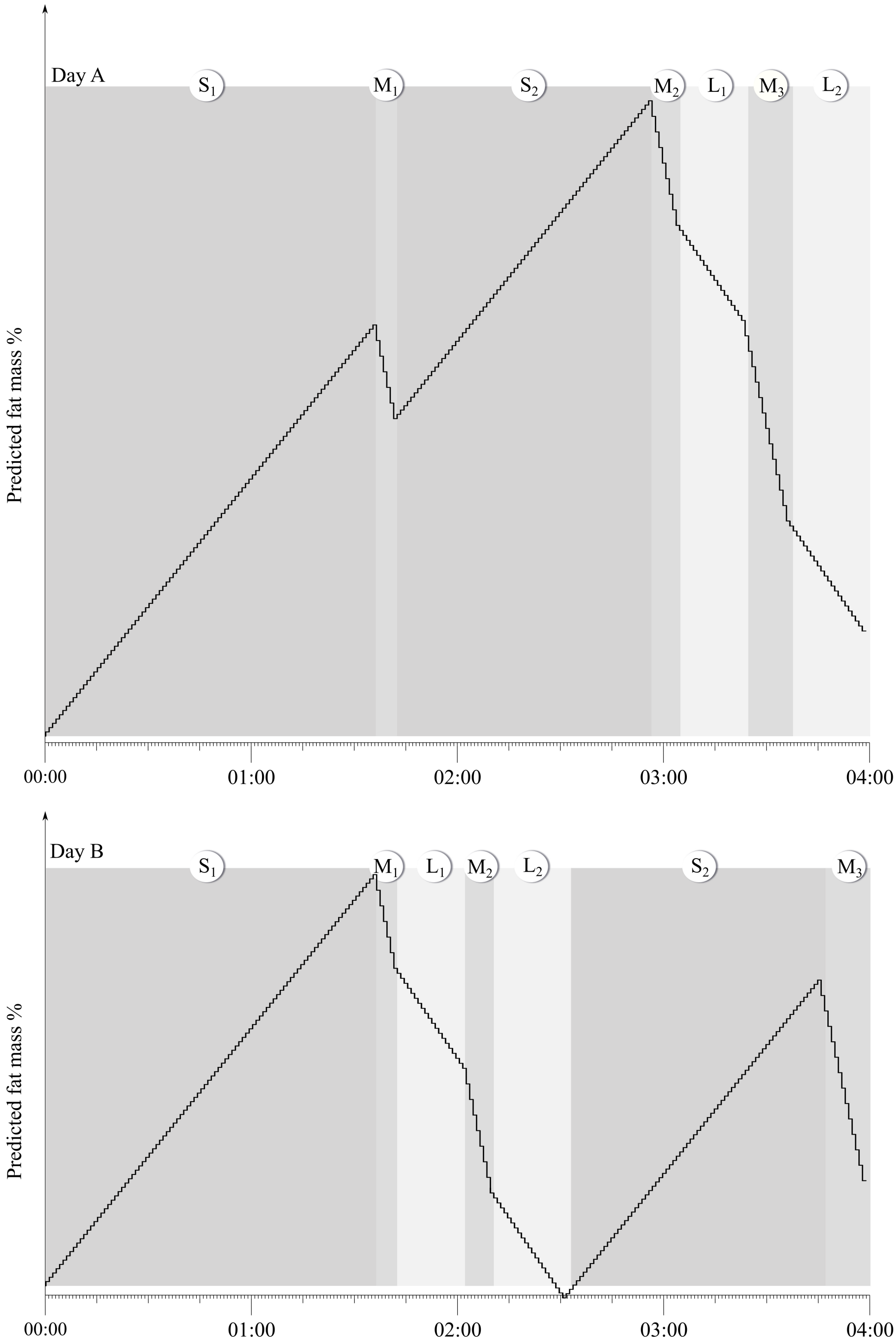

Figure 1. The SPORT algorithm illustrated with segments of two days with identical number and durations of physical behavior bouts but different sequential orders. S = sedentary behavior bout; L = light physical activity bout; M = moderate-to-vigorous physical activity bout. At the beginning of the day, the running value X_0 is 0, and with each additional minute *i* (or another time unit), the running value X_i adapts.

Methods

All materials and supporting documents are available at the Open Science Framework (OSF) repository at https://osf.io/k8nrq/?view_only =9a7a6dfc2be94d118b8f06edfd96786c.

Design

The data in the current study are from a cohort of Dutch adolescents (11-15 years) from the Focus on Strength randomized controlled trial (2014-2016) which examined the effects of strength exercises and motivational sessions on physical activity and body composition (Ten Hoor et al., 2016). Participants wore the Actigraph GT3x (Actigraph, Pensacola, FL, USA) accelerometer for one week at baseline and after 12 months follow up (Ten Hoor et al., 2016; Ten Hoor et al., 2018). Since too few adolescents had data at both timeslots, we only considered the baseline data but conducted sensitivity analyzes with the post-test data.

Data collection

Nine Dutch Schools were recruited via the school managements. Of the 808 students, 113 declined. Among the 695, 435 participants had accelerometer data for at least four days of at least 7 hours (see “measurements and procedure” for details), and 397 participants remained after the exclusion of outliers. Written informed consents were obtained by the schools. Participants and their parents were informed about the study and were allowed to withdraw from the study at any time. The study was approved by the Ethics Review Committee of the Faculty of Psychology and Neuroscience, Maastricht University, the Netherlands [ERCPN-05-09-2012A1].

Measurements and procedure

The student administrations of the schools provided the adolescents’ gender and date of birth. Standard procedures to measure anthropometrics were used (Centers for Disease Control and Prevention (CDC)). Height (SECA

213 stadiometer, Hamburg, Germany) and weight (SECA 877 scale, Hamburg, Germany) were measured to the nearest 1 mm and 0.1 kg, respectively. Participants took off shoes and heavy clothes during measurements. We calculated BMI as weight/height squared ($kg{\cdot}m^{-2}$) and BMIz from age- and sex specific reference values (Fredriks et al., 2000). Body composition was assessed by deuterium dilution (Schoeller et al., 1986; Westerterp et al., 1995), and fat-free mass was calculated using age-specific hydration fractions (Lohman, 1989). Compared to underwater weighing, deuterium dilution is validly measures body composition (van der Kooy et al., 1992; Westerterp et al., 1991).

To assess physical behaviors, students wore the Actigraph GT3x on their lower back for five days (including schooldays and at least one weekend day) except during water activities (Plasqui, 2017; Plasqui et al., 2013; Yngve et al., 2003). The accelerometer was attached by an elastic belt. Accelerations were read with a rate of 30 Hz and reintegrated with an output data rate of 15-second epochs (Banda et al., 2016; Evenson et al., 2008). We used Actilife (v6.13.3; https://www.actigraphcorp.com/actilife/) to scan the raw data and determine wear times by using the vertical axis counts (counts per minute; CPM) and a minimum non-wear time window of 90 minutes (Choi et al., 2012). When making decisions on wear-time cut-off values, there is a trade-off between reliability and sample retention (Toftager et al., 2013). Therefore, an analysis was performed to determine a high wear time cut-off while keeping a maximum of analyzable data points. We created datasets with all possible cut-offs and tested for differences of participant characteristics (i.e., age, sex, BMIz) of those datasets compared to characteristics of the original sample using Wilcoxon-Sign-Ranked tests (see OSF repository). This resulted in establishing 7-hours per day for a minimum of 4 days cut-off. We classified SB (≤ 100 CPM), LIPA (101 to 2295 CPM) and MVPA (≥ 2296 CPM) (Evenson et al., 2008; Trost, Loprinzi, Senso, & Pfeiffer, 2009). Before aggregating the raw data by dates and user identifiers, we subtracted 4 hours from the time stamps. Thereby, we ensured that behaviors being performed after midnight but before sleeping time would still be analyzed with the waking day before participants went to bed.

Statistical analyses

We computed descriptive univariate statistics and assessed the distributions of the variables using histograms and QQ plots. Non-normally distributed variables were reported as medians and Inter-Quartile-Ranges (*IQR*), normally distributed variables as means (*M*) and standard deviations (*SD*). Physical behaviors were reported as compositional geometric means and log-ratio variances (i.e. “the variances of the logarithms of all pair-wise ratios between parts”) (Chastin, Palarea-Albaladejo, et al., 2015). These values consider the co-dependence between the three physical behaviors all being compositional parts of the waking day (Aitchison, 1982; Chastin, Palarea-Albaladejo, et al., 2015).

In order to analyze the performance of the SPORT algorithm, we used linear regression models with either CoDA, the $\text{SPORT}_{\text{constant}}$ or the $\text{SPORT}_{\text{linear}}$ variables as predictors. Normalized BMI (i.e. BMI *z*-scores) and %FM constituted the outcome variables. We then compared the predictive power of the SPORT models with the CoDA models by comparing the explained variances (adjusted R squared) and by testing the differences of predictive power by means of likelihood ratio tests.

We checked for covariations using backwards elimination starting with age and gender as covariates and retained them as a predictor if the *p*-value was less than .20. Consequently, we controlled for age and gender (locked in the models) when predicting BMIz scores, and for gender when predicting %FM. Outliers that were detected in either of the variables from the models (CoDA, $\text{SPORT}_{\text{constant}}$, or $\text{SPORT}_{\text{linear}}$) were excluded from all models. All tests for statistical significances were two-sided, with a type I error at $p < .05$ and effect sizes were calculated using 95% confidence intervals (CI). Data cleaning and inferential analyses were performed using R version 3.4.1. The outcomes of the models were evaluated using 5-fold cross-validation, where datasets are divided into five groups of nearly equal number of data points. Each group was taken as test dataset in one of the five iterations. The remaining groups constituted the training set, on which the models were fit before being evaluated on the test set (Kuncheva, 2014). For readability, we only report the results of the cross-validation; the results of the regression models without cross-validation can be retrieved from the additional material.

Compositional analyses

Waking days are composed of three behaviors: SB, LIPA and MVPA, of which the proportions will always add up to 100% of the wearing time. Increasing the amount of one of these behaviors necessarily yields a decline in the two other behaviors. Hence, each behavior is always seen in relation to the proportion spent in the other two behaviors. CoDA regression models are based on isometric log-ratio data transformations, to adjust for time spent in other behaviors (Chastin, Palarea-Albaladejo, et al., 2015). Thereby, the daily proportions spent in SB, LIPA, and MVPA are each transformed into isometric log-ratios by adjusting them for the proportions spent in the other two behaviors. Three regression models each incorporating one of the three physical behaviors as the first part of the composition (e.g. $z1_{SB} = \sqrt{2/3}\ \ln\left(SB\%/\sqrt{LIPA\%\ x\ MVPA\%}\right)$), and another physical behavior as the second part (e.g. $z2_{LIPA} = \sqrt{1/2}\ \ln\left(LIPA\%/\sqrt{MVPA\%}\right)$) constitute the basis of the CoDA approach, whereby all of the three behaviors are once the first and once the second part of the composition. We used the log-ratio Expectation-Maximization algorithm to impute the zeros in the 115 days (5.48% of all days) that adolescents had not collected any MVPA (Palarea-Albaladejo & Martín-Fernández, 2008; Palarea-Albaladejo & Martín-Fernández, 2015). This allowed to calculate log-ratios, while preserving the log-ratios between the other behaviors. Although sleep is a health behavior that is of importance, in the first version of the SPORT algorithms, we focused on physical activity and sedentary behavior.

SPORT algorithms

The SPORT algorithms are based on a running value X_i. Each day starts with $X_0 = 0$. Depending on the physical behavior being performed, X_i is increased or decreased. In the example pattern in figure 2, X_i might decrease when being active in periods M_1 and L_1 and might worsen when sitting in S_2.

In each minute (or another time unit) i, X_i is a result of a cumulative adaption: $X_{i-1} + a_{i-1}$, where a_{i-1} represents the amount of change (~ size of the step).

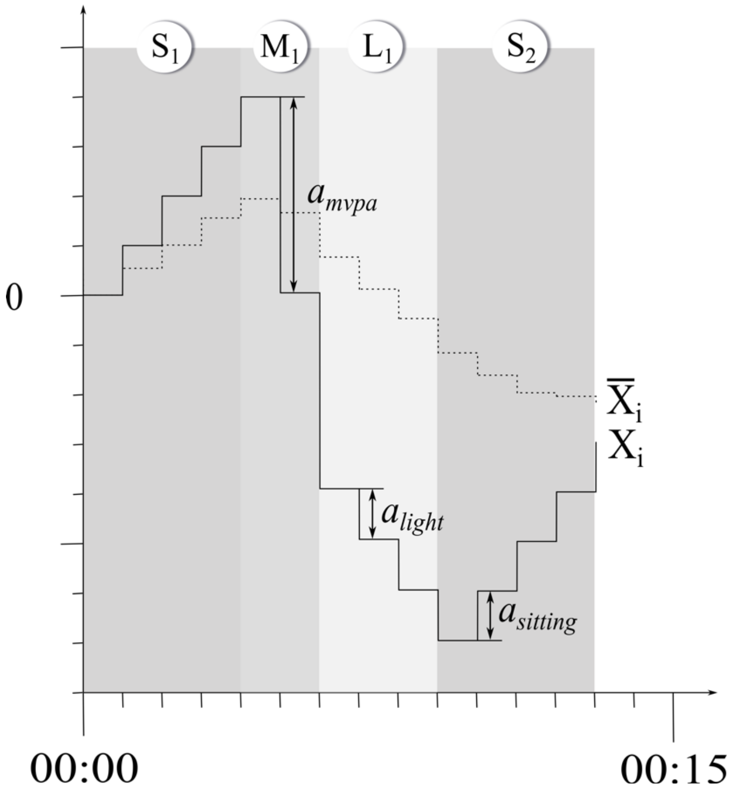

Figure 2. Intensity dependent accumulation of the running value. When predicting BMIz and when being active, the running value X_i (solid line) is assumed to decrease ($a_{LIPA} < 0$ and $a_{MVPA} < 0$). When being sedentary, the running value is assumed to increase ($a_{SB} > 0$). With each additional running value X_i, the average running value $\overline{X}_i$ adapts (dotted line).

Amount of change as behavior dependent constant - SPORT $_{Constant}$

The average of the running values $\bar{X}_i$ of all waking minutes (i.e. time units) n will be the independent variable when predicting health outcomes:

$$BMIz = \beta_0 + \frac{\sum_0^n X_i}{n} \quad (1)$$

With each minute, X_i adapts by an activity-dependent amount of change a_i:

$$BMIz = \beta_0 + \frac{X_0 + (X_0 + a_0) + (X_0 + a_0 + a_1) + \cdots + \left(X_0 + \sum_0^{n-1} a_i\right)}{n} \quad (2)$$

In equation (2), X_0 is 0, since each day starts with a running value of 0. Additionally, n is known as an individual's amount of collected minutes. Therefore, the behavior dependent amounts of change (a_i) and the intercept β_0 are the only unknown variables. The amount of the change a_{i-1} affecting X_i depends on the physical behavior performed in minute *i-1*. We assume that SB is detrimental and should have a worsening effect. Therefore, when predicting BMIz (higher ~ less healthy), a_{SB} should be a positive number. Accordingly, a_{LIPA} and a_{MVPA} should be negative. Therefore, a_i is determined by the function

$$a_i = f(Activity\_Category) = \begin{cases} a_{SB}, & i \text{ is spent in } SB \\ a_{LIPA}, & i \text{ is spent in } LIPA \\ a_{MVPA}, & i \text{ is spent in } MVPA \end{cases} \quad (3)$$

By the help of matrix calculations, a_{SB}, a_{LIPA} and a_{MVPA} can be isolated in such a way that simple linear regression analyses can help to get these a-values (see additional files):

$$BMI_z = \beta_0 + a_{SB}\frac{U_{SB}}{n} + a_{LIPA}\frac{U_{LIPA}}{n} + a_{MVPA}\frac{U_{MVPA}}{n} \quad (4)$$

U_{SB}, U_{LIPA} and U_{MVPA} from equation (4) can be retrieved by multiplying three matrixes (see equation 5): 1) an all-ones matrix with 1 row and n columns, 2) a binary lower triangular matrix (n rows, n columns) with all values above the diagonal being 0, and all values below and including the diagonal being 1, and 3) a binary matrix with n rows and 1 column with Boolean values for SB, LIPA or MVPA. In the last matrix, the first row is always 0, and the last row represents the second-to-last minute of a day. For example, for calculating U_{SB}, if the *i-1th* (e.g., first) minute of a day was spent sitting, the *ith* (e.g., second) row is 1, and 0 if it was spent in LIPA or in MVPA. U_{LIPA} and $U_{MVPA}$are calculated accordingly.

$$U_{SB} = [1 \ \dots \ 1]_{1,n} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{n,n} \begin{bmatrix} 0 \\ S_0 \\ \vdots \\ S_{n-1} \end{bmatrix}_{n,1} \quad (5)$$

If participants have multiple days of data, they have multiple U_{SB}s, U_{LIPA}s and U_{MVPA}s. These are each added up, and the three results are divided by the total amount of collected minutes on all days.

Amount of change as behavior-dependent function of time in bout - SPORT$_{linear}$

The amount of change a_i affecting the running value X_i might also depend on the time spent in a certain bout. We assume for SB that the running value is increasing and that this amount of increase is steeper the longer the person has been sitting. Accordingly, we assume $A_{SB}(t_i), A_{LIPA}(t_i)$ and $A_{MVPA}(t_i)$ to be linear functions of the time spent in the concerning bout $A_{SB}(t_i) = \gamma_o + \gamma_1 t_i$, $A_{LIPA}(t_i) = \delta_0 + \delta_1 t_i$, and $A_{MVPA}(t_i) = \varepsilon_0 + \varepsilon_1 t_i$. Assumingly, the intercept γ_o will be positive (X_i rises when sitting), and δ_0 and ε_0 will be negative. We assume that the slope γ_1 in function $A_{SB}(t_i)$ will be positive (the rise of X_i is bigger, the longer a person is sitting in a row). Furthermore, we assume that the size of the benefit of spending time in physical activity decreases or stays the same by the time spending in the bouts (Quinn, Klooster, & Kenefick, 2006; Tarp et al., 2018). Thus, we assume the slopes δ_1 and ε_1 to be either positive or zero. Figure 3 visualizes the difference between the SPORT$_{constant}$ and the SPORT$_{linear}$ algorithm. Summarized, a_i is determined by the function:

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$$a_i = f(t_i) = \begin{cases} A_{SB}(t_i) = \gamma_0 + \gamma_1 t_i\,, \ i \text{ is spent in } SB \\ A_{LIPA}(t_i) = \delta_0 + \delta_1 t_i\,, \ i \text{ is spent in } LIPA \\ A_{MVPA}(t_i) = \varepsilon_0 + \varepsilon_1 t_i\,, \ i \text{ is spent in } MVPA \end{cases} \quad (6)$$

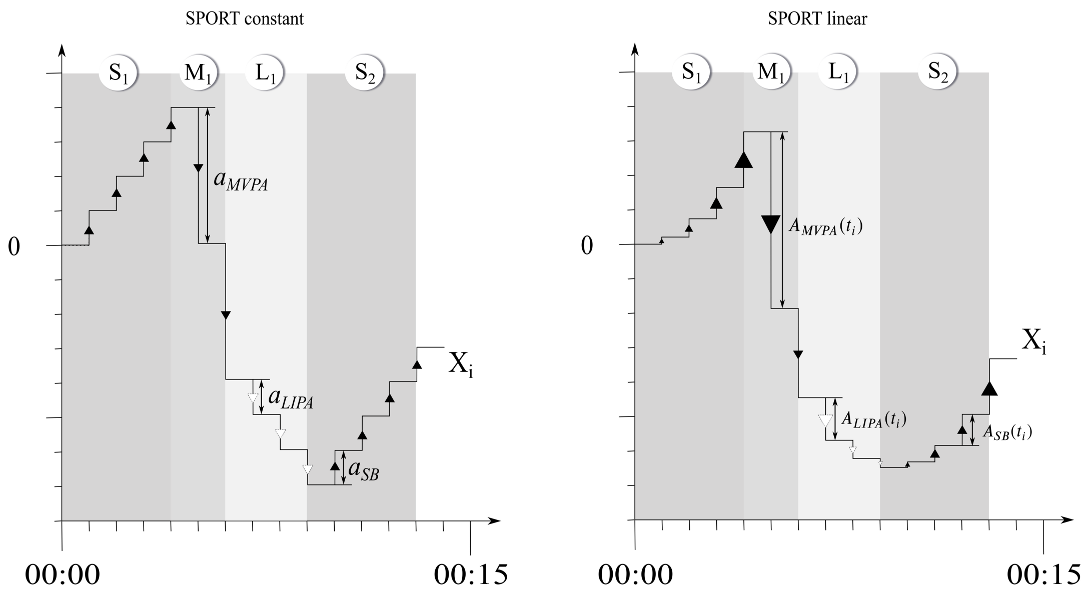

Figure 3. Representation of the difference between the SPORT$_{constant}$ and SPORT$_{linear}$ algorithm. When predicting BMIz with the SPORT$_{constant}$ algorithm, the running value X_i is assumed to change by a constant a_{SB}, a_{LIPA} or a_{MVPA} depending on the behavior being performed. When predicting BMIz with the SPORT$_{linear}$ algorithm, the running value X_i is assumed to change by a linear function of time in bout $A_{SB}(t_i)$, $A_{LIPA}(t_i)$ or $A_{MVPA}(t_i)$ depending on the behavior being performed and on the time having spent in the concerning SB, LIPA or MVPA bout.

The process to isolate the six unknown variables $(\gamma_0, \gamma_1, \delta_0, \delta_1, \varepsilon_0, \varepsilon_1)$ is described in the additional materials. The resulting regression formula is:

$$BMI_z = \beta_0 + \gamma_0 \frac{V_{SB}}{n} + \gamma_1 \frac{W_{SB}}{n} + \delta_0 \frac{V_{LIPA}}{n} + \delta_1 \frac{W_{LIPA}}{n} + \varepsilon_0 \frac{V_{MVPA}}{n} + \varepsilon_1 \frac{W_{MVPA}}{n} \quad (7)$$

V_{SB}, V_{LIPA} and V_{MVPA} are known and can be calculated like it is done to get U_{SB}, U_{LIPA} and U_{MVPA} (see equation 5). W_{SB}, W_{LIPA} and W_{MVPA} are calculated similarly, but the last factor includes information about the time t_i that was spent in the concerning bout until minute i:

$$W_{SB} = [1 \;\; \dots \;\; 1]_{1,n} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{n,n} \begin{bmatrix} 0 \\ S_0 t_0 \\ \vdots \\ S_{n-1} t_{n-1} \end{bmatrix}_{n,1} \quad (8)$$

Results

The descriptive statistics are displayed in table 1. Of all 695 participants, 595 wore the accelerometer, and 397 provided 7 hours of accelerometer data each for at least 4 days. BMIz was available in all of the 397 (218 females, 179 males) adolescents, and 260 (153 females, 107 males) adolescents provided urine samples to have their %FM measured. The variability of the compositional physical activity data is displayed with pair-wise log-ratio variances. A log-ratio variance close to zero refers to a high proportional relationship of the two behaviors: SB and LIPA were highly co-dependent; the time spent in MVPA was relatively independent of the time spent in SB.

Table 1. Descriptive characteristics of participants.

	Female	**Male**	**Total**
	***n* = 218**	***n* = 179**	***N* = 397**
Age, mean (*SD*)	12.4 (0.5)	12.5 (0.6)	12.4 (0.6)
Physical activity			
Wear time, median (*IQR*)	735.5 (251)	720.2 (263.8)	726.5 (257.8)
SB (min · d^{-1}, median, *IQR*)	531 (184.5)	510.5 (183.2)	521 (184.8)
SB compositional *GM* (%), log-ratio variances LIPA, MVPA	77.8 (0.1, 0.4)	77.6 (0.1, 0.4)	77.7 (0.1, 0.4)
LIPA (min · d^{-1}, median, *IQR*)	160.5 (85.4)	160 (91.4)	160 (87.8)
LIPA compositional *GM* (%), log-ratio variances SB, MVPA	22.2 (0.1, 0.2)	22.4 (0.1, 0.2)	22.3 (0.1, 0.2)
MVPA (min · d^{-1}, median, *IQR*)	24.2 (24.6)	28.4 (31.6)	25.8 (27.2)
MVPA compositional *GM* (%), log-ratio variances SB, LIPA	0 (0.4, 0.2)	0 (0.4, 0.2)	0 (0.4, 0.2)
Meeting guidelines (Nr of days per individual) [a]	0.4 (0.8)	0.8 (1.1)	0.6 (1)
Anthropometrics			
Height (cm), mean (*SD*)	159.5 (7.2)	160.2 (9.6)	159.8 (8.4)
Weight (kg), mean (*SD*)	50.9 (10.7)	48.7 (11.6)	49.9 (11.2)
BMI (kg · m^{-2}), median (*IQR*)	19.9 (3.5)	18.8 (3.2)	19.4 (3.4)
BMIz, median (*IQR*)	0.3 (1.1)	0.1 (1.2)	0.2 (1.2)
%FM, median (*IQR*)	26.8 (7.6)	22.6 (7.9)	25.1 (8)
Underweight, n (%)	24 (11)	33 (18.4)	57 (14.4)
Normal weight, n (%)	129 (59.2)	109 (60.9)	238 (59.9)
Overweight, n (%)	49 (22.5)	22 (12.3)	71 (17.9)
Obese, n (%)	16 (7.3)	15 (8.4)	31 (7.8)

Abbreviations: *SD*, standard deviation; *IQR*, inter-quartile-range; *GM*, geometric mean; min · d^{-1}, minutes per day; BMI, body mass index; %FM, fat mass percentage; SB, sedentary behavior; LIPA, light physical activity; MVPA, moderate-to-vigorous intensity physical activity.

[a] Meeting guideline is defined as the average number of days, that participants accumulated at least 60-minutes of MVPA.

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Regression results of the CoDA approach

Table 2 presents the results of the CoDA models. After cross-validation, the amount of variance being explained by the CoDA models was low when predicting BMIz ($R^2_{adjusted}$ = .02) and when predicting %FM ($R^2_{adjusted}$ = 0.05) (J. Cohen, 1988). None of the parts each in relation to the other parts (i.e. isometric log ratios) was significantly associated with the outcomes.

Table 2. Compositional (CoDA) behavior models for BMIz (controlled for age and gender) and %FM (controlled for gender)

	BMIz				*%FM*			
	N = 397				*n* = 260			
Physical activity [a]	β	*SE*	*p*	95% CI	β	*SE*	*p*	95% CI
Compositional data analysis								
$z1_{SB}$	0.20	0.26	.44	-0.31, 0.71	1.02	2.17	.59	-3.26, 5.31
$z1_{LIPA}$	0.07	0.34	.70	-0.59, 0.74	-3.16	2.82	.31	-8.73, 2.40
$z1_{MVPA}$	-0.28	0.17	.14	-0. 62, 0.06	2.14	1.43	.19	-0.69, 4.97
Intercept	-3.31	1.48	.04	-6.21, -0.41	29.12	2.94	< .001	23.32, 34.91

Abbreviations: BMIz, Body Mass Index z-score; %FM, fat mass percentage; β, coefficient; *SE*, standard error; CI, confidence interval; SB, sedentary behavior; LIPA, light physical activity; MVPA, moderate-to-vigorous intensity physical activity; Int, intercept.

$$z1_{SB} = \sqrt{2/3}\ \ln\left(SB\%/\sqrt{LIPA\%\ x\ MVPA\%}\ \right))$$

$$z1_{LIPA} = \sqrt{2/3}\ \ln\left(LIPA\%/\sqrt{SB\%\ x\ MVPA\%}\ \right))$$

$$z1_{MVPA} = \sqrt{2/3}\ \ln\left(MVPA\%/\sqrt{LIPA\%\ x\ SB\%}\ \right))$$

Regression results of the SPORT algorithms

SPORT_{constant}

Table 3 presents the results of the linear regressions using the $SPORT_{constant}$ algorithm. When cross-validating, the amount of variance being explained by the $SPORT_{constant}$ models was low when predicting BMIz ($R^2_{adjusted}$ = .01), and low-to-moderate when predicting %FM ($R^2_{adjusted}$ =.05) (J. Cohen, 1988). Likelihood ratio tests showed no significant improvement for the

$SPORT_{constant}$ models compared to the CoDA models when predicting BMIz (p = .10) and when predicting %FM (p = .43). When considering the specific behaviors, minutes of MVPA were negatively associated with BMIz (β = -0.56; SE = 0.25; p = .05; 95% CI = -1.06, -0.06), while sedentary minutes and light physical activity minutes did not show significant associations with BMIz. None of the physical behaviors was associated with %FM.

Table 3. SPORTconstant models for BMIz (controlled for age and gender) and %FM (controlled for gender)

	BMIz (*N* = 397)				*%FM* (*n* = 260)			
Physical activity [a]	β[a]	*SE*[a]	*p*	95% CI[a]	β[a]	*SE*[a]	*p*	95% CI[a]
SPORT (constant-type)								
SB	0.02	0.04	.62	-0.07, 0.10	0.02	0.36	.78	-0.69, 0.74
LIPA	0.05	0.09	.58	-0.12, 0.22	0.30	0.75	.65	-1.18, 1.78
MVPA	-0.56	0.25	.05	-1.06, -0.06	-2.88	2.31	.24	-7.43, 1.67
Intercept	-280	150	.09	-576, 16	2727	421	< .001	1897, 3557

Abbreviations: BMIz, Body Mass Index z-score; %FM, fat mass percentage; β, coefficient; *SE*, standard error; CI, confidence interval; SB, sedentary behavior; LIPA, light physical activity; MVPA, moderate-to-vigorous intensity physical activity; Int, intercept.

[a] Since these values are very small, considering the predictors each being 15 seconds of an entire day, these values are presented as x * 10^2, to read 0.23, instead of 0.00 after rounding.

$SPORT_{linear}$

Table 4 presents the results of the linear regressions using the $SPORT_{linear}$ algorithm. When cross-validating, the amount of variance being explained by the $SPORT_{linear}$ models was low-to-moderate when predicting BMIz ($R^2_{adjusted}$ = .06), and moderate when predicting %FM ($R^2_{adjusted}$ =.09) (J. Cohen, 1988). Likelihood ratio tests showed significant improvements of the $SPORT_{linear}$ model compared to the CoDA models when predicting both BMIz and %FM (p < .001). Minutes of LIPA were negatively associated with BMIz (β = -0.55; SE = 0.22; p = .03; 95% CI = -0.98, -0.11). The time-in-bout dependent association of LIPA minutes with BMIz was positive (β = 0.16; SE = 0.04; p < .001; 95% CI = 0.08, 0.24). None of the other physical behaviors or time in bouts were associated with BMIz. When predicting %FM, the time-in-bout

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dependent association of LIPA minutes with %FM was positive (β = 1.20; *SE* = 0.33; *p* < .01; 95% CI = 0.56, 1.85). None of the other physical behaviors was associated with %FM.

Table 4. $SPORT_{linear}$ models for BMIz (controlled for age and gender) and %FM (controlled for gender)

Physical activity	*BMIz* (*N* = 395)				*%FM* (*n* = 260)			
	β[a]	*SE*[a]	*p*	95% CI[a]	β[a]	*SE*[a]	*p*	95% CI[a]
SPORT (linear-type)								
SB	0.06	0.06	.31	-0.05, 0.18	0.38	0.50	.46	-0.60, 1.36
SB (time in bout)	0.00	0.00	.65	0.00, 0.00	0.00	0.01	.75	-0.02, 0.01
LIPA	-0.55	0.22	.03	-0.98, -0.11	-3.84	1.87	.06	-7.53, -0.16
LIPA (time in bout)	0.16	0.04	< .001	0.08, 0.24	1.20	0.33	< .01	0.56, 1.85
MVPA	0.04	0.42	.72	-0.78, 0.86	-4.99	3.51	.19	-11.92, 1.94
MVPA (time in bout)	-0.05	0.05	.34	-0.16, 0.05	0.77	0.42	.09	-0.05, 1.59
Int.	-327	146	.04	-615, -39	2547	434	< .001	1692, 3402

Abbreviations: BMIz, Body Mass Index z-score; %FM, fat mass percentage; β, coefficient; *SE*, standard error; CI, confidence interval; SB, sedentary behavior; LIPA, light physical activity; MVPA, moderate-to-vigorous intensity physical activity; Int, intercept.

[a] Since these values are very small, considering the predictors each being 15 seconds of an entire day, these values are presented as x * 10^2, to read 0.23, instead of 0.00 after rounding.

Discussion

The $SPORT_{linear}$ models showed a better predictive power compared to the CoDA models. In this study, most of the models explained low to low-to-moderate amounts of variance when predicting BMIz. Previous studies that applied the CoDA approach with similar target groups, showed similar results when predicting BMIz (Carson, Tremblay, Chaput, McGregor, & Chastin, 2019; Talarico & Janssen, 2018). Yet, when using waist circumference as proxy for %FM, other studies found 4-29% of explained variances when using the CoDA approach (Carson et al., 2019; Talarico & Janssen, 2018). The reasons for the negligible amounts of explained variance for %FM in the current study might root in considerably fewer participants when predicting

%FM or in the fact that, in this study, sleep was not included as predictor as opposed to other studies. The findings show that it might be very important to consider daily sequential patterns when giving physical activity guidelines or when predicting health.

When examining the associations of the single physical behaviors (SB, LIPA and MVPA) with the outcomes in the SPORT models, most of the associations between the physical behaviors and the outcomes were as expected. In the $\text{SPORT}_{\text{constant}}$ models, minutes in MVPA showed a beneficial association with BMIz. In the $\text{SPORT}_{\text{linear}}$ models, minutes in LIPA were beneficially associated with both outcomes. However, the longer LIPA bouts were, the less beneficial this impact was. Therefore, for BMIz and %FM, LIPA minutes seem to be most beneficial when collected in short bouts. Indeed, some researchers found that regular interruptions of SB with LIPA or standing is at least equally effective compared to accumulating MVPA with equal energy expenditure within one bout (Duvivier et al., 2013; Duvivier et al., 2017). Interestingly, we found adverse, yet not significant, estimates for MVPA in the $\text{SPORT}_{\text{linear}}$ models. The longer MVPA bouts were, the more beneficial time spent in MVPA was for BMIz. Adversely, minutes in MVPA were beneficially associated with %FM, but this benefit decreased by the time spent within MVPA bouts. Therefore, concerning %FM, MVPA seems to be more beneficial when collected in many short bouts as opposed to one long bout, while concerning BMIz, MVPA seems to be more beneficial when collected in longer bouts. These results are in line with previous research stressing the crucial role of replacing SB with LIPA and MVPA (Aadland, Kvalheim, Anderssen, Resaland, & Andersen, 2018; Fairclough et al., 2017). However, it remains unclear, whether MVPA should better be collected in many shorts or in fewer long bouts.

The SPORT algorithm is an adequate method to represent sequential physical behavior patterns on a minute-by-minute basis, and might, therefore, be helpful when giving real-time feedback (e.g., in SB interventions). Recommendations should consider a balance between value, context and focus: Although presumably, sitting will need to be reduced to a minimum, this will hardly be realizable in all contexts. For example, in an office environment (context), the maximum allowable average running value (i.e. X_i in the SPORT algorithm) will then be higher not to result in potentially disturbing getting-up-reminders (focus on prevention). In contrast, when having interventions with a target group from a rehabilitation institution (context), it is not only about maintaining health but about recovering from a disease, therefore, the average allowed running value should be lower (focus on cure). The application of the SPORT algorithm in real-time interventions should be investigated in future studies. The current paper describes an approach that can be applied in various contexts with different focuses.

Both approaches, the CoDA and the SPORT algorithms that were applied in the current paper respect the collinearities that come with physical activity data. Although BMIz might not fully represent the healthiness of body compositions (Bogin & Varela-Silva, 2012), the measurements allowed for a recruitment of a representative sample from a relatively difficult setting (high schools). Furthermore, the measurements of the independent as well as the dependent variables where objectively measured by using accurate and valid tools. Lastly, we considered not only the complex and sequential nature of physical behavior patterns, but we also considered the lengths of the specific bouts ($\text{SPORT}_{\text{linear}}$ models) that might be of relevance (e.g., sitting becomes even more harmful, the longer it gets (Carter et al., 2017); standing still might be very healthy in the beginning but the effects diminish, the longer one stands). The focus of this paper is on presenting a way to represent physical behavior patterns in a single value. However, when coming up with physical activity pattern recommendations, longitudinal data should be used, to allow casual inferences. Since there is first evidence, that standing breaks, besides physical activity breaks, can have a beneficial impact on health (Chastin, Egerton, Leask, & Stamatakis, 2015), measurement tools should be applied that are able to distinguish between postures, such as VitaBit, ActivPAL or the Actigraph being worn on the thigh (Atkin et al., 2012; Berninger et al., 2018). Since we aimed for a simplified and interpretable guideline on physical behaviors, we did not include sleeping time and we merged all intensity levels above moderate activity into one category (MVPA). However previously, contradictory associations between different intensities within the MVPA spectrum and cardiometabolic health were found and the importance of considering sleep was addressed (Aadland, Kvalheim, Anderssen, Resaland, & Andersen, 2019; Carson et al., 2019; Chastin, Palarea-Albaladejo, et al., 2015; Howard et al., 2015). The SPORT algorithm is very flexible, and it can be applied to more or less fine-grained data using 10 or 60 second epochs, using more intensity levels of physical activity, and including sleep as additional component.

The SPORT algorithm might be a suitable method for representing complex physical activity patterns and their sequential order within a single value. If other physical activity researchers succeed in representing their data in a long format data frame (several rows per individual, each row representing one minute of the day), it is easy to use a single function to transform their data into SPORT variables (e.g. with R, excel, or SPSS) that can be inserted into regression models. Compared to an approach considering all physical behaviors of the waking day, additionally considering the sequential nature of SB, LIPA and MVPA yielded in higher amounts of explained variances when predicting BMIz and %FM among a cohort of Dutch adolescents. The results from this study further support the hypothesis that it might be rather the point in time than the intensity of physical activity that matters when interrupting sitting. To satisfy the “T” (target group-specific) and the “O” (outcome-specific) in the SPORT acronym, future studies are needed that apply the SPORT algorithm to other target groups predicting other and more specific (i.e., more sensitive, or minutely measurable) biomarkers.

CHAPTER 6

The effects of UPcomplish on sedentary behavior, quality of life, and psychosocial determinants: A stepped-wedge design

Berninger, N. M., Plasqui, G., Crutzen, R., Ruiter, R. A. C., Kok, G., & ten Hoor, G. A. (2020). The effects of UPcomplish on sedentary behavior, quality of life, and psychosocial determinants: A stepped-wedge design (Submitted for publication)

Abstract

Objectives. Sedentary behavior (SB) affects cardiometabolic health and quality of life (QoL). We examine the effects of UPcomplish, a 12-week data-driven intervention, on SB, QoL, and psychosocial determinants among office workers.

Methods. Five groups starting with time-lags of seven weeks (n = 142, 96 females) received the 14 feedback messages (FBMs). Participants received questionnaires at the beginning, middle, and end of the intervention and continuously wore an accelerometer measuring SB, operationalized as proportions (compositional data approach, CoDA) and summed squared sitting bouts (SSSB). We used linear mixed-effects models with random intercepts for weeks (between-subjects) and individuals (within-subjects).

Results. UPcomplish did not reduce SB. Within-subjects compared to baseline, FBM #3 (β_{CoDA} = 0.24, p < .001, 95% CI [0.15, 0.33]; β_{SSSB} = 20.83, p < .001, 95% CI [13.90, 27.28]) and #4 (β_{CoDA} = 0.20, p < .001, 95% CI [0.11, 0.29]; β_{SSSB} = 24.80, p < .001, 95% CI [15.84, 33.76]) increased SB. QoL was unaffected. Perceived susceptibility (i.e. sitting more than recommendation) was lower after FBMs #6 to #8 ($\beta_{between}$ = -0.66, p = .04, 95% CI [-1.03, -0.30]; β_{within} = -0.75, p = .02, 95% CI [-1.18, -0.32]). Within-subjects, intentions to sit less were higher after FBMs #1 to #5 (1.14, p = .02, 95% CI [0.61, 1.66]). Improvements in determinants and in SB were not associated, nor were improvements in SB and in QoL.

Conclusions. Compared to VitaBit only, UPcomplish was not beneficial. Environmental restructuring (e.g. standing desks) might be superior. Analyses of moderators of effectiveness are warranted.

Trial registration: NL7503 – registered 1 February 2019.

Introduction

Diabetes type 2, cardiovascular disease (Biswas et al., 2015; Van Uffelen et al., 2010; Wilmot et al., 2012), and mental health problems (Hamer & Stamatakis, 2014; Voss et al., 2014) are examples of the consequences of sedentary behavior (SB). SB refers to sitting, lying or reclining behaviors (excl. sleeping) that exhibit low energy expenditures (Tremblay, Aubert, et al., 2017). Modernization yielded a higher prevalence of SB and office workers accumulate about 11 hours of SB per day (Clemes et al., 2014; Ryan et al., 2011). Unsurprisingly, office workers have higher mortality rates compared to workers in more active occupations (Chau et al., 2015). The negative health effects of SB cannot be compensated by meeting the guidelines for moderate-to-vigorous physical activity (MVPA) (Bankoski et al., 2011; Ekelund et al., 2016; Hamilton et al., 2008). Except for amounts of more than 10 hours, not the sitting time per se is detrimental, but a pattern with bouts of long, uninterrupted SB (Bankoski et al., 2011; Healy et al., 2008). Indeed, regular SB interruptions of standing and light activity with the same energy expenditure as single bouts of MVPA seem to be at least equally effective in reducing cardiometabolic risk (Duvivier et al., 2013; Duvivier et al., 2017).

During SB, the muscles of the lower limbs are static, which reduces the blood flow, downregulates the endothelial functions, and increases inflammation (Carter et al., 2017). These cardiovascular and inflammatory aspects yield physical problems but also impact brain health and quality of life (QoL). For example, SB involves low muscle contractions suppressing the lipoprotein lipase in red muscle fibers (Hamilton et al., 2008). Ineffective triglyceride metabolism and visceral fat increase insulin resistance and reduce binding of leptin in the hypothalamus and hippocampus, which is responsible for synaptic plasticity (Voss et al., 2014). Moreover, cerebral blood flow and the release of neurotrophins are reduced during SB (Wennberg et al., 2016). These mechanisms might impair cognitive functioning, vitality and thus performance (Hendriksen et al., 2016). Furthermore, prolonged SB increases the pressure on the intervertebral disks and weakens posterior lumbar structures, explaining its link to increased intensities of lower back pain

(Alzahrani, Alshehri, Al Attar, & Alzhrani, 2019; S.-M. Chen, Liu, Cook, Bass, & Lo, 2009), and to neck and upper extremity musculoskeletal symptoms (Coenen et al., 2019). Lastly, despite unclarities of the mechanisms, SB was linked to stress and mental health problems (Faulkner & Biddle, 2013; Kilpatrick, Sanderson, Blizzard, Teale, & Venn, 2013; Rebar, Duncan, Short, & Vandelanotte, 2014).

Despite evidence of successful SB interventions, existing effective interventions require environmental changes such as standing desks or personal coaches (Coffeng et al., 2012; Kwak et al., 2007; McEachan et al., 2008). A more cost-efficient way than a personal coach to tailor an intervention is by using technology. Platforms, where individuals can communicate via text and multimedia files, provide a solution for delivering tailored coaching messages at reduced costs (Broekhuizen et al., 2012; Kelders et al., 2012; Schoeppe et al., 2016). Previous computer-tailored SB interventions have already shown reductions in workplace SB, which was not found, when analyzing the effects on both working and leisure time SB (De Cocker, De Bourdeaudhuij, Cardon, & Vandelanotte, 2016). Therefore, a personal coach that provides tailored but automated feedback might be the optimal mixture of a low-cost yet personal intervention. We developed a data-driven SB intervention aimed at a reduction of SB among office workers: UPcomplish (Berninger et al., 2020).

The Intervention Mapping (IM) protocol is a comprehensive framework guiding the systematic development of behavior change interventions (O'Cathain et al., 2019), and workplace physical activity interventions that have been developed with IM yielded promising effects (Coffeng et al., 2014; Kwak et al., 2010; McEachan et al., 2008). The first version of UPcomplish was developed using evidence from the literature and from theories (e.g. Reasoned Action Approach (Fishbein & Ajzen, 2011)). Thereby, the problem of SB was refined (e.g. prevalence, consequences, detrimental sitting patterns), and behavioral outcomes, and performance objectives (i.e. sub-behaviors), were formulated. Important and changeable psychosocial determinants (e.g. attitude, perceived behavioral control) were gathered and linked to the performance objectives by the help of matrices. The cells contain specific change objectives that define the change that is needed in the determinants to realize the performance objectives. These change objectives constitute the basis for selecting behavior change methods and creating the content of the program. Interventions that effectively reduced SB mostly applied a combination of behavior change methods (Stephenson et al., 2017). These methods can change the determinants if they are translated into practical applications by the help of parameters for use (Kok et al., 2016). For example, the method *"consciousness raising"* can help to change the determinant "*attitude"*. A negative attitude towards too much sitting will increase the likelihood of a person deciding to reduce his/her SB. This will only be effective if the rise of awareness (i.e. of negative consequences of SB), is rapidly followed by an increase in self-efficacy (i.e. feeling capable to solve the problem) (Bartholomew Eldredge et al., 2016). Pre-tests of intervention components facilitated further refinement of UPcomplish. A pilot test of the complete intervention was conducted before automatizing the 14 feedback messages (FBMs) enabling program implementation on a larger scale. Applying the IM protocol resulted in a logic model of the intervention that illustrates the causal chain from the practical applications and theoretical methods used in the intervention to reduced SB (Berninger et al., 2020).

The main component of the intervention is "UPcomplish", which consists of 14 FBMs remotely provided by a coach. The messages aim at changing self-efficacy, attitude, social support, perceived susceptibility, and normative beliefs by the help of tailored feedback and motivational support. For example, by providing participants with positive feedback on their goal achievements they feel supported, which can facilitate sitting reductions (Gardner et al., 2016). The UPcomplish component requires little resources from the coach since the content automatically tailors to participants' activity patterns. The second component, the VitaBit toolkit, serves as a monitoring toolkit. The accelerometer is worn in trouser pockets or at the thigh and collects data on participants' SB and physical activity behavior (Berninger et al., 2018). These data are synchronized via Bluetooth with the VitaBit mobile phone application when participants open the app. The app includes tools to monitor SB, such as a "Vitality score" (0 = unhealthy SB pattern, 100 = healthy SB pattern), the current amount of SB, and goal achievements.

This study investigates the effects of UPcomplish on objectively measured SB, on self-reported QoL (i.e. perceived performance, stress, pain, emotional well-being, vitality), and on psychosocial determinants (i.e. attitude, perceived social support, perceived behavioral control, perceived susceptibility, intention). Between and within subjects, we expect UPcomplish to reduce the daily proportion of SB and prolonged sitting when compared to baseline. Furthermore, we expect improvements in QoL and in the psychosocial determinants. We chose a stepped-wedge design (Figure 1) above a parallel randomized control trial to reduce the burden for participants in a potential waiting control group (e.g. compliance), to increase statistical power (i.e. groups act as both control and intervention group; continuously measured SB) (Hemming, Haines, Chilton, Girling, & Lilford, 2015), and to gather seasonal spread data.

Methods

This study was pre-registered: NL7503 (https://www.trialregister.nl/trial/7503). The intervention protocol can be found in (Berninger et al., 2020). The cleaned raw data and additional material is fully disclosed in the supplementary materials (https://osf.io/qzp9m/?view_only=30ada8d6fc0e4ac19a1610b8901f9f96). We adhere to the Consolidated Standards of Reporting Trials (CONSORT) checklist of information to include when reporting a stepped wedge cluster randomized trial (Hemming et al., 2018).

Study design and sample

Five intervention groups (Figure 1) of maximum 40 participants started with time lags of approximately 7 weeks (exact duration of the time lags depended on holidays and availability of participants). The 12-week intervention began with a kick-off (incl. generic information on SB and the health consequences) and a baseline week serving as the control condition, where participants wore the VitaBit. To create a personal atmosphere and considering time constraints but still be efficient, the kick-offs were held for different sub-groups (i.e. companies) with a maximum of 15 and a minimum of 5 participants. The sub-groups were continuously recruited starting in one of the upcoming kick-offs that they would be available. If many participants per group dropped out, sub-groups were merged to still allow for group activities (e.g. challenges, group report). Participants were eligible to take part in the study if they were able to stand and walk, and willing to download the VitaBit application on their smartphones (with at least Android 4.3 or iOS 8.1). Furthermore, only people who defined themselves as office workers and who understand the German language could participate.

All individuals were compared to their baseline week (within-subjects' comparisons). Some of the calendar weeks included participants being at their baseline and participants having already received the intervention (between-subjects' comparisons). To disentangle the effects of the 14 FBMs, the reception of all FBMs were analyzed in separate regression models. For example, in calendar week 27, 42 participants have worn the VitaBit device. Among these, 20 participants were still in their baseline week, and 12 had just received FBM #5. When analyzing the between-subjects' effect of FBM #5, these 12 participants were compared to the 20 participants being in their baseline week. To increase statistical power, the FBMs were aggregated when analyzing the effects on psychosocial determinants and QoL, since these variables were assessed via surveys, which were only distributed three times: at baseline (T0), in week 6 (T1), and at the end of the intervention (T2).

For the time of the evaluation (May 2019 - January 2020), we had 200 VitaBit sensors to our disposal. With an anticipated drop-out rate of 20% and five intervention groups (32 participants per group after drop-out and the middle group providing data for both baseline and intervention), we expected to end with a sample size of 192, which would reveal sufficient power according to our sample size planning (Berninger et al., 2020). We contacted as many German companies as resources allowed (number not noted) via contact persons, personal conversations, emails, and phone calls. Only companies being recruited via contact persons or personal conversations

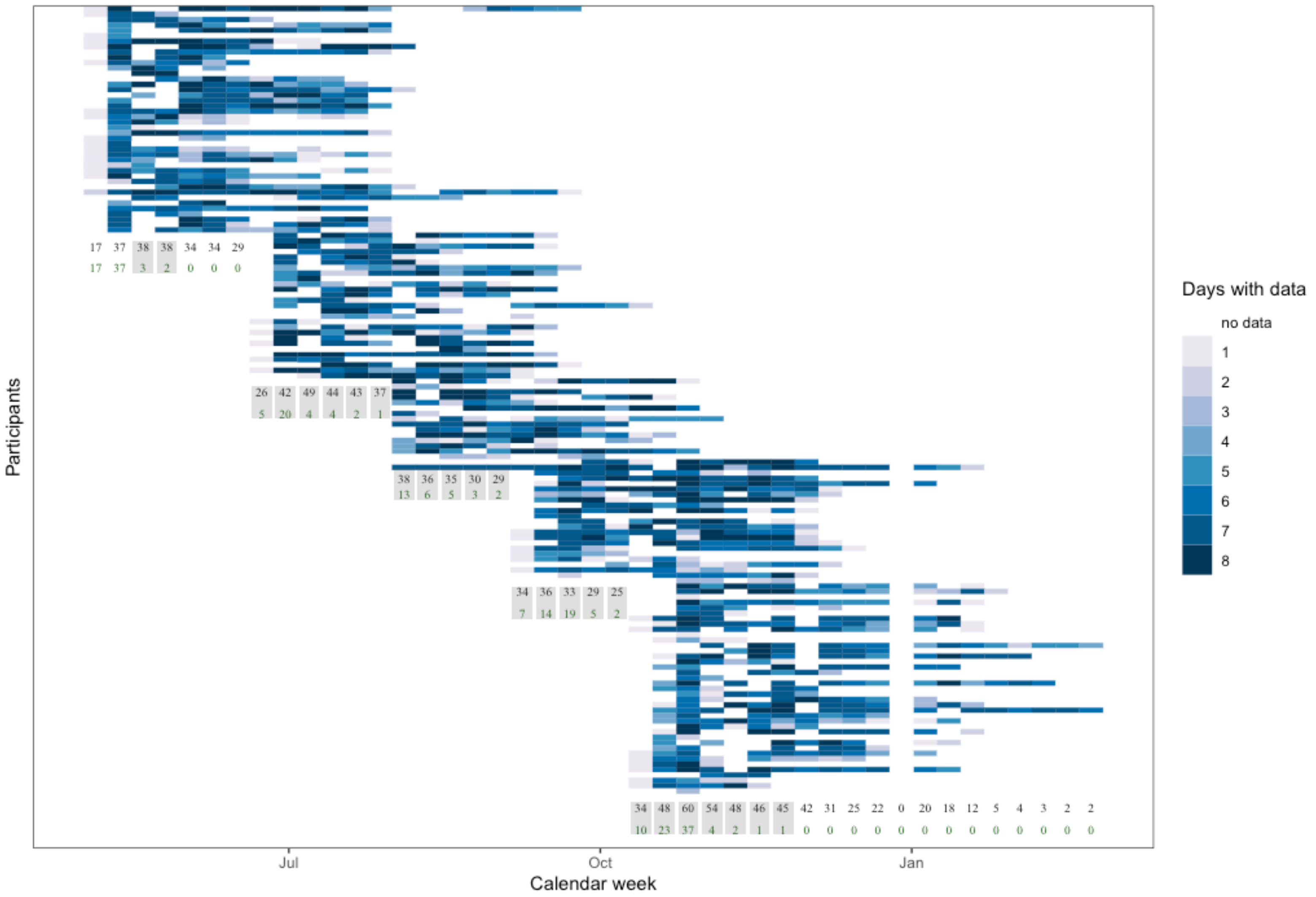

Figure 1. Flow chart of the stepped-wedge trial of the UPcomplish intervention. The black numbers indicate per week, how many participants provided data; the green numbers how many participants were in their baseline phase during the concerning week. Weeks with both baseline and intervention data, which are relevant for the between-subjects' comparisons, are marked with grey cuboids.

showed interest in participating. In total, 193 desk workers of companies from different industries (e.g. public service, automotive, education, social service, information technology) were willing to participate starting in one of 15 sub-groups (4 sub-groups in intervention group 1, 2 sub-groups in intervention groups 2, 3 and 4, and 5 sub-groups in intervention group 5). Of the eligible participants, 43 declined before the kick-offs or did not create an account. Of the 150 participants with an account, 142 started with the baseline week (i.e. wore the VitaBit). The survey was filled out by 129 (91%), 67 (47%), and 62 (44%) participants at T0, T1, and T2, respectively. The VitaBit was worn by 109 (75%) and 82 (56%) participants for at least 6 and 9 weeks, respectively.

Participants could refuse participation at all times, without giving a reason. Yet, most participants that dropped out gave a reason (e.g. technical problems, time constraints). This study and its consent procedure was approved by the Ethics Review Committee of the Faculty of Psychology and Neuroscience, Maastricht University, the Netherlands [ERCPN-188_11_02_2018]. The trial was pre-registered under: NL7503.

Procedure

Recruitment

The UPcomplish coach (psychologist employed by VitaBit software) was trained by the intervention developers and distributed the flyer among potential participants. The flyers included information on what would be expected from participants (e.g. downloading the VitaBit application), and how much time participation would require (i.e. 1 hour kick-off, 14 x 2 minutes feedback, and 3 x 20 minutes surveys). Additionally, it included information about inclusion criteria (e.g. being a desk worker, able to walk) and about the benefits one could expect from participation (e.g. vitality through a reduction of SB). Interested participants and contact persons forwarded the flyer to colleagues and supervisors. As soon as the management of the companies agreed, the contact person provided the coach with the email addresses of volunteering participants, and they arranged a date for the kick-off. The participants were invited to the kick-offs via email and received an instruction on the creation of a VitaBit account, the information sheet and the informed consent.

Kick-off and baseline measurement

For the kick-offs, the UPcomplish coach visited the participants in their companies. The duration depended on the size of the concerning sub-group and the number of questions but ranged between 35 and 60 minutes. The meetings started with an introduction including an estimation of participants' daily sitting times (on workdays and on days off). This was followed by an explanation about the consequences of SB and by information about how UPcomplish could help them to reduce SB. Afterwards, participants were told to choose a realistic but challenging goal (e.g. sitting for a max. of 8 hours per day), which would be adapted after the baseline week if necessary. These goals served as orientation for the participants and as basis to give first tailored advice[1]. The coach explained the functionalities of the VitaBit toolkit and clarified questions. Written informed consent was obtained. The VitaBit devices were distributed and connected via Bluetooth with the application on the smartphones. Interested participants who were not able to make it to the kick-off received an email with the information and hand-outs in order to participate in the study as well. At the end of the kick-off, the participants were instructed to start wearing the VitaBit device. The week after the kick-off served as baseline and involved the first survey on QoL and on determinants. Afterwards, participants received the intervention including the second survey in week 6 and the last survey after the intervention. As a compensation, they received an individual and a group report (i.e. at company level) and a 50€ VitaBit voucher. The 4 weeks after the intervention served as follow-up measurement, before the devices were collected.

[1] Note: Although the intervention and the advice focused on the reduction of SB (e.g. drink more to sit less), participants could also set a physical activity goal (e.g. being active for at least 1 hour per day), which enabled a provision of choice. Participants with physical activity goals received similar feedback on SB patterns (e.g. your sitting bouts are the longest on Tuesday mornings) but different feedback on the achievement of goals (e.g. you reached your goal of moving at least 1 hour on Wednesday).

Intervention

The protocol of the intervention and the link between the intervention messages and the psychosocial determinants are described elsewhere (Berninger et al., 2020).

UPcomplish

For each FBM, the authorized coach downloaded the raw data (pseudonymized identifiers and physical behavior) from the VitaBit server. The data were imported into R statistical software where the concerning code cleaned and transformed them in such a way, that it provided the coach with tailored messages for all participants (either with the next FBM or with a reminder). The coach remotely delivered the FBMs through the participants' preferred communication-channel (WhatsApp or email). At the beginning, participants received two FBMs per week, which was reduced to one FBM per week as of week 6 (see Table 1 for an overview of the FBMs). The FBMs were not delivered, if a participant had dropped out, was on a holiday (only if they indicated to pause for their holidays), or if not enough VitaBit data were available (i.e. depending on the FBM less than 1 to 3 days à 6 hours of data). If insufficient data were available on a feedback day, instead of receiving the next FBM, they received a reminder to synchronize their data or were asked if they still participated (maximum two reminders in a row). In case a participant received a reminder or did not receive any message, the concerning FBM was sent in the week after and the following FBMs were delayed also. FBMs #13 (*Competing colleagues*) and #14 (*Tips how to keep new habits in the future*), however, were not delayed and sent to all active participants at the same points in time. Therefore, if participants missed two FBMs due to holiday or because they forgot to wear the device, they received FBMs #1 to #10, #13, and #14. Based on the baseline data and the goals from the kick-off meeting, the goals were adapted if necessary and broken down into graded sub-goals. In addition to feedback about their goals, participants received tailored FBMs about their SB pattern (e.g. *[…] From your data, I detected something interesting about your sitting pattern […]: On Tuesday noons between 11:00 and 14:00[…], your sitting periods seem to be specifically long. Here is a tip […]*),

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they were asked about individual hurdles to reduce sitting (e.g. *What hinders you most when reducing your sitting behavior? Is it habits, lack of time, […]?*), and they received tailored tips to overcome the hurdles that they mentioned. Furthermore, the FBMs included activity challenges in biweekly circles. The last two weeks focused on sustaining the new behavior where the coach suggested to participants to make if-then-plans and to get a SB buddy.

Table 1. Overview of the FBMs of the UPcomplish intervention

		Delivery[a]
#1	*Goal adaption and sub-goals*	Monday, week 2
#2	*Feedback sitting pattern and first challenge*	Thursday, week 2
#3	*What are your hurdles to sit less?*	Monday, week 3
#4	*Tips how to overcome hurdles*	Thursday, week 3
#5	*Feedback on goal achievement*	Monday, week 4
#6	*Feedback sitting pattern and second challenge*	Thursday, week 4
#7	*Goal adaption and long-term goal*	Monday, week 5
#8	*Feedback on sitting pattern and on goal achievement*	Thursday, week 5
#9	*Feedback goal achievement and third challenge*	Thursday, week 6
#10	*Did your hurdles change?*	Thursday, week 7
#11	*Feedback goal achievement and last sub-goal*	Thursday, week 8
#12	*Feedback sitting pattern and fourth challenge*	Thursday, week 9
#13	*Competing colleagues*	Thursday, week 10
#14	*Tips how to keep new habits in the future*	Thursday, week 11

[a] Point in time if device is worn at all points in time

Measures

Behavioral measurements

Physical behavior

Physical behavior was measured throughout the intervention using accelerometry (Atkin et al., 2012). The VitaBit sensor (3.9 × 1.4 × 0.85 cm, 4.8 g) was worn in trouser pockets or at the thigh (i.e. if no pockets were available, attached with a magnet). The battery life of the device is at least 30 days, and it shows sensitivity and specificity values of 85.7% and 91.2%, respectively, for SB (Berninger et al., 2018). The device deploys a sampling rate of 33 Hz and has an output data rate of 30 seconds. The data are stored on the device for at least 30 days and can be synchronized with the VitaBit application (requiring at least iOS 7.1/Android 4.3) via Bluetooth. Via wireless Internet, the data are sent to a back-end server, where they are processed and stored (pseudonymized) in a time series database. An authorized coach can retrieve them from the VitaBit portal.

Performance objectives

The performance objectives (e.g. participants create a VitaBit account) were retrieved from behavioral observations. These will be analyzed as potential moderators of effectiveness in a future article and are described in more detail elsewhere (Berninger et al., 2020).

Online survey

The survey was distributed at baseline (T0), after 6 weeks (T1), and after the intervention (T1). Sociodemographic and job-related variables were measured at T0, intervention characteristics (e.g. acceptability, understandability) at T2. Psychosocial determinants and QoL were measured at all three time points. We translated the Individual Work Performance Questionnaire into German using back-translation since we were not aware of any validated German version (Brislin, 1970). As indicators for reliability, we present Omegas (ω) if more than 2 items were used for a construct, and Pearson correlations (*r*) if only two items were used (Crutzen & Peters, 2017; Revelle & Zinbarg, 2009).

Demographic, educational and job-related variables

VitaBit obtained gender, age, education, height, weight, and job-related variables when participants created the account. They could choose between 8 educational degrees (e.g. Master's degree), between 29 job titles (e.g. sales, administrative), between 17 company industries (e.g. service, finance), and between different team sizes. In the survey at T0, they were asked about the usual number of workdays per week (from 1 to 7; 1 item), about employment status (full-time/part-time; 1 item) and about job tasks (5 items). These included phone calls, computer work, desk work, having meetings, and travelling/visiting clients, e.g. *"How much - on average per day (in %) - do you estimate that you spend on the following tasks? Phone calls?"* (De Cocker et al., 2015).

Quality of life

Task and contextual performance were assessed by subscales of the Individual Work Performance Questionnaire (seldom = 0 to always = 5). Task performance (5 items; ω = .72) refers to the ability of performing the tasks being required for the job, operationalized as work quantity and quality or job skills, e.g. *"During the last week, I was able to perform my work well with minimal time and effort"*. Contextual performance (9 items; ω = .57) refers to the organizational, social, or psychological requirements facilitating functioning at work, such as investing effort or cooperating, e.g. *"I took on extra responsibilities."* (Koopmans et al., 2014). Stress perception was administered by the Perceived Stress Scale (10 items; e.g. *"How often have you felt nervous and 'stressed'?"*; ω = .89) (S. Cohen et al., 1994; Klein et al., 2016). Bodily pain (2 items; e.g. *"How much bodily pain have you had?"*; r = .85), emotional well-being (5 items; e.g. *"How much of the time have you been a happy person?"*; ω = .83), and vitality (4 items; e.g. *"How much of the time did you have a lot of energy?"*; ω = .86) were assessed by subscales of the SF-36 (Ware Jr, 2000).

Psychosocial determinants

We assessed the psychosocial determinants by questions about how much they agreed with certain statements. The items for attitudes (6 items; e.g. *"[…] walking around at work is healthy"*; ω = .62), perceived social support (2 items; e.g. *"[…] walking around at work is encouraged by my colleagues"*; r = .62), perceived behavioral control (4 items; e.g. *"I am sure that I can […] walk around at work, even though I feel bad, tired, tense or depressed"*; ω = .70), and intention (2 items; e.g. *"Are you planning to interrupt long sitting periods at work with […] walking breaks?"*; r = .43) were based on former evaluation papers (De Cocker et al., 2015). Additionally, we assessed perceived susceptibility, which refers to the belief to be at risk of getting a disease (2 items; e.g. *"My daily sitting time is more compared to what is recommended."*; *r* = .72) (Champion & Skinner, 2008; J. Kim & Park, 2012).

Data preparation

Activity and survey data were merged using pseudonymized user identifiers. Afterwards, information on when the individuals received which FBM was added. Since the three physical behavior levels are multicollinear (e.g. more sitting always results in less standing and walking), we applied a compositional data analysis approach (CoDA) to transform them into non-interdependent variables (Busschaert et al., 2015). We transformed the daily sitting proportions into isometric log-ratios by adjusting for the proportions spent in the other two behaviors (i.e. $z1_{sitting} = \sqrt{2/3}\ \ln\left(Sitting\%/\sqrt{Standing\%\ x\ Activity\%}\right)$) (Chastin, Palarea-Albaladejo, et al., 2015). To analyze the effects on prolonged sitting, we used the sum of the squared sitting bouts (SSSB) (Berninger et al., 2020). To weigh longer sitting bouts more than shorter bouts, daily sitting bouts are squared before being summed up ($SSSB = \sum_0^n SitBout_i^2$). Afterwards, the data were cleaned to retain only those days that a participant collected enough data. Since there is always a trade-off between the retention of a high number of days and the retention of long days (Toftager et al., 2013), we inspected the data by a plot: how many days would be retained for which daily wear time cut-off. Each stricter wear time cut-off resulted in fewer analyzable days. The wear time cut-off of 8 hours per day seemed to be a turning point (see Figure 2, Appendix A): each additional hour of required wearing time drastically reduced the number of available days. Therefore, only days with at least 8 hours of VitaBit data were retained. Holidays were excluded from the analyses.

Therefore, 14 variables were created with Boolean values representing whether the concerning FBM was already received at the concerning point in time, e.g. FBM_4_Received (TRUE/FALSE/NA). These variables were FALSE, if a participant had not received any FBM (i.e. baseline week), and TRUE, if a participant had received the concerning FBM (e.g. #4). The variables were NA, if a participant had received more or less FBMs than the concerning FBM. The

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NAs were removed in the regression models to disentangle intervention effects from all other FBMs. Therefore, the reception of FBM #4 (i.e. FBM_4_Received = TRUE) was compared against baseline (i.e. FBM_4_Received = FALSE). For each individual, the days were averaged by FBM, for example, all days after FBM #4 but before #5 were averaged. Outliers were excluded using the Mahalanobis distance method (generalized squared distance), which is used for multidimensional data and is defined as the distance of each point (row in the matrix) from a distribution, normalized by the standard deviation, and adjusted by the covariances of the variables (Mahalanobis, 1936).

Data analyses

We performed descriptive univariate analyses and used histograms and QQ plots to assess the distribution of the data. Non-normally distributed variables were reported as medians and Inter-Quartile-Ranges (IQR), normally distributed variables as means and standard deviations (SD), and categorical variables as absolute numbers and percentages.

To examine the between-subjects' effects of UPcomplish on SB, QoL, and psychosocial determinants, we used linear mixed-effects models with random intercepts for calendar week (which was dropped for QoL and the determinants, due to singularity). For comparability, all outcome variables were centered around the baseline sub-group means, and non-normally distributed variables (i.e. SSSB) were transformed to a normal distribution using square roots. For assessing within-subjects' effects, the outcome variables (SB, QoL, and determinants) were centered around calendar week means (of baseline data), before deploying linear mixed-effects models with random intercepts for user identifier.

Tests for statistical significance were two-sided with an alpha of .05, which was corrected using the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995; Benjamini & Yekutieli, 2001). We used R version 3.4.1 to clean and analyze the data. We used backwards elimination to select the covariates (retention if $p < .20$). As potential covariates we included age, gender, body mass index (BMI), education, work tasks, working model, and weekly working days. As a result, we controlled for gender (locked in the model) when analyzing the intervention effects on SB. For all other models, no covariates were included.

Results

Participant characteristics

A total of 142 participants (96 females) wore the VitaBit device at baseline (Table 2). Participants had a median age of 42.0 (interquartile range [IQR] = 21.5) years and a mean BMI of 23.1 (standard deviation [SD] = 4.6) kg/m^2. Of the participants, who filled out the survey, 104 (73%) worked full-time, and 21 (15%) part-time. The majority (*n* = 113, 80%) worked 5 days per week. At baseline, 63 (44%) participants met the program goal: maximally sitting for 8 hours, minimally standing and walking for 4 hours, and having a maximum of 18.8*10^3 SSSB on at least 30% of the days (incl. weekend) (Berninger et al., 2020).

During the intervention, 33 participants dropped out due to technical problems (n = 10), because they lost their device (n = 6), or due to other reasons, like time constraints (n = 17). Of the baseline participants, 109 participants (77%) stayed in the program until the end as indicated by still having data available and not having indicated to stop the intervention. The number of people having received the nth FBM decreased from FBM #1 (n = 141 [99% of the baseline participants]) to FBM #12 (n = 29, 20%). FBMs #13 (n = 78, 55%) and #14 (n = 69, 49%) were sent to all participants having data at the concerning points in time even if they had message delays. Figure 3 displays the number of participants having been sent FBMs to.

Table 2. Descriptive characteristics of participants at baseline

	Female	Male	Total
	n = 96	n = 46	n = 142
Age (years), median (IQR)	41.0 (20.5)	44.0 (19.5)	42.0 (21.5)
Job related variables			
Education level, n (%)[a]			
None	11 (11)	3 (7)	14 (10)
Secondary school	17 (18)	10 (22)	27 (19)
Professional	43 (45)	23 (50)	66 (46)
Work status, n (%)			
Full-time	65 (68)	39 (85)	104 (73)
Part-time	20 (21)	1 (2)	21 (15)
Workdays per week, n (%)			
4 workdays	7 (7)	2 (4)	9 (6)
5 workdays	76 (79)	37 (80)	113 (80)
6 workdays	0 (0)	3 (7)	3 (2)
Physical behavior[b]			
Wear time (min d^{-1}), mean (SD)	835.7 (102.0)	797.8 (115.2)	823.4 (107.5)
Sedentary (min d^{-1}), median (IQR)	504.4 (96.5)	522.3 (92.7)	510.2 (95.3)
Sedentary compositional geometric mean[c], log-ratio variances standing, walking	62.3 (0.3, 0.2)	67.7 (0.2, 0.2)	64.3 (0.3, 0.2)
Standing (min d^{-1}), median (IQR)	224.8 (129.7)	161.3 (73.2)	199.6 (102.8)
Standing compositional geometric mean[c], log-ratio variances sitting, walking	27.2 (0.3, 0.2)	19.4 (0.2, 0.1)	24.5 (0.3, 0.3)
Activity (min d^{-1}), median (IQR)	83.9 (45.6)	105.2 (37.8)	91.7 (45.7)
Activity compositional geometric mean[c], log-ratio variances sitting, standing	10.5 (0.2, 0.2)	12.9 (0.2, 0.1)	11.3 (0.2, 0.3)
Program goal achieved (CER), n (%)	49 (51.0)	14 (30.4)	63 (44.4)
Anthropometrics[d]			
Height (cm)	168.6 (6.9)	180.5 (6.7)	172.4 (8.8)
Weight (kg)	65.0 (13.0)	80.0 (14.0)	69.0 (19.0)
BMI (kg/m^2)	22.3 (5.1)	24.8 (3.5)	23.1 (4.6)
Underweight, n (%)	5 (5)	2 (4)	7 (5)
Normal weight, n (%)	46 (48)	14 (30)	60 (42)
Overweight, n (%)	16 (17)	14 (30)	30 (21)
Obese, n (%)	4 (4)	0 (0)	4 (3)

Abbreviations: SD, standard deviation; IQR, interquartile range; min d^{-1}, minutes per day; % d^{-1}, proportion of the day; CER, control event rate.

[a] As indicated during the process of account creation.

[b] Estimates of physical behaviors are estimated via VitaBit accelerometry. Control event rate: Maximum 8 hours sitting, minimum 4 hours standing and walking, $18.8*10^3$ SSSB on at least 30% of the days incl. weekend.

[c] The percentage of the day is the estimated proportion of wearing-minutes spent in each activity level.

[d] Underweight defines as BMI <18.5, Normal weight 18.5-25, overweight 25-30, obese > 30

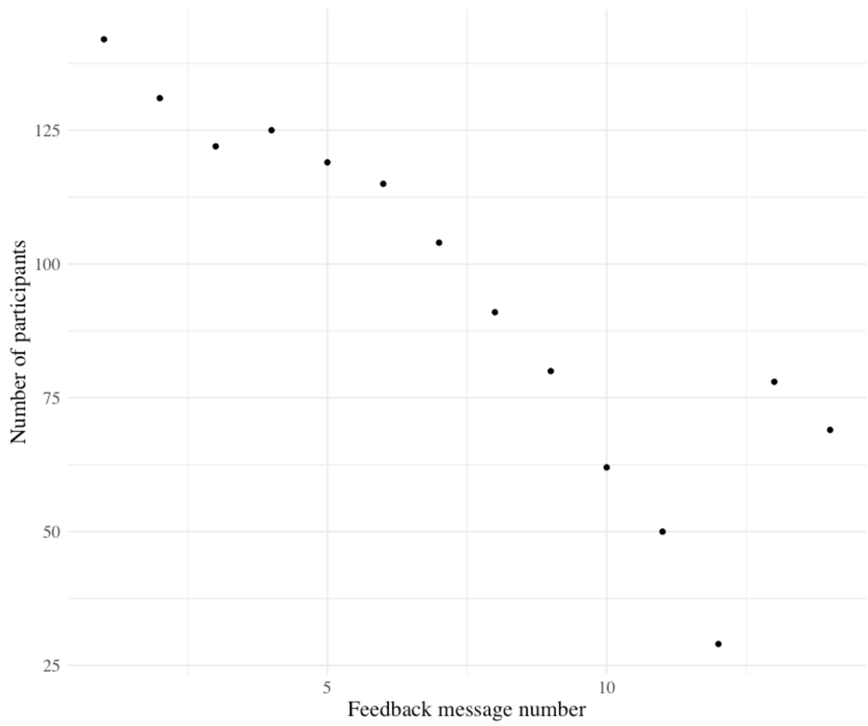

Figure 2. Number of participants having received specific feedback messagess of UPcomplish

Effects of UPcomplish on sedentary behavior

Between-subjects, UPcomplish did not result in a significant reduction of SB (Table 3). Within-subjects (Table 6, Appendix B), compared to baseline, participants were significantly more sedentary when they had received FBM #3 (β_{CoDA} = 0.24 [SE = 0.05; 95% CI = 0.15, 0.33; $p = p_{corrected} < .001$]; β_{SSSB} = 20.83 [SE = 3.53; 95% CI = 13.90, 27.28; $p = p_{corrected} < .001$]) and #4 (β_{CoDA} = 0.20 [SE = 0.05; 95% CI = 0.11, 0.29; $p = p_{corrected} < .001$]; β_{SSSB} = 24.80 [SE = 4.56; 95% CI = 15.84, 33.76; $p = p_{correctetd} < .001$]).

Effects of UPcomplish on quality of life

Neither between-subjects (Table 4) nor within-subjects (Table 7, Appendix C) did the intervention reveal significant effects on QoL.

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Table 3. Multilevel linear models for the effects of different exposures to the UPcomplish intervention on SB[a]

		SB CoDA		*Summed Squared Sitting Bouts*	
Intervention [b]	n [c]	β *(SE)*	95% CI	β *(SE)*	95% CI
1	*145*	-0.01 (0.08)	-0.16, 0.15	1.25 (6.68)	-11.79, 14.29
Intercept	*(116, 29)*	-0.03 (0.07)	-0.17, 0.12	-5.50 (6.06)	-17.33, 6.34
2	*148*	-0.01 (0.07)	-0.14, 0.12	-4.67 (5.15)	-14.72, 5.38
Intercept	*(107, 41)*	-0.06 (0.06)	-0.17, 0.06	-8.35 (4.52)	-17.18, 0.47
3	*149*	0.01 (0.07)	-0.12, 0.14	-5.00 (5.32)	-15.39, 5.38
Intercept	*(90, 59)*	-0.08 (0.06)	-0.19, 0.02	-8.44 (4.40)	-17.03, 0.16
4	*111*	-0.02 (0.08)	-0.17, 0.13	4.30 (6.87)	-9.10, 17.70
Intercept	*(74, 37)*	-0.11 (0.06)	-0.24, 0.02	-11.67 (5.82)	-23.02, -0.32
5	*114*	0.03 (0.07)	-0.12, 0.18	3.98 (6.78)	-9.77, 17.07
Intercept	*(20, 94)*	-0.05 (0.04)	-0.12, 0.03	-5.42 (3.73)	-13.20, 1.72
6	*126*	-0.12 (0.07)	-0.26, 0.03	-9.26 (5.80)	-21.07, 1.85
Intercept	*(29, 97)*	-0.03 (0.05)	-0.12, 0.07	-2.45 (3.78)	-9.76, 5.19
7	*141*	-0.09 (0.06)	-0.21, 0.03	-0.34 (5.54)	-11.05, 9.99
Intercept	*(40, 101)*	-0.03 (0.04)	-0.10, 0.04	-3.55 (3.56)	-9.89, 3.23
8	*134*	-0.04 (0.06)	-0.17, 0.07	-3.57 (5.60)	-14.90, 7.15
Intercept	*(35, 99)*	-0.01 (0.04)	-0.08, 0.06	-1.35 (3.87)	-8.79, 6.56
9	*119*	0.01 (0.07)	-0.14, 0.14	-3.05 (6.00)	-15.25, 7.77
Intercept	*(35, 84)*	-0.02 (0.06)	-0.10, 0.08	-2.47 (4.65)	-8.50, 6.20
10	*96*	-0.03 (0.08)	-0.18, 0.11	-0.28 (6.53)	-13.23, 12.31
Intercept	*(38, 58)*	-0.04 (0.06)	-0.16, 0.07	-5.41 (5.47)	-16.44, 5.13
11	*45*	0.00 (0.12)	-0.25, 0.24	5.82 (8.94)	-13.16, 22.94
Intercept	*(29, 16)*	-0.12 (0.11)	-0.32, 0.09	-8.76 (12.50)	-33.83, 17.22
12	*18*	0.22 (0.26)	-0.32, 0.66	17.24 (19.88)	-23.27, 52.44
Intercept	*(12, 6)*	-0.05 (0.26)	-0.55, 0.44	-18.68 (19.55)	-55.46, 18.19
13	*8*	0.01 (0.16)	-0.33, 0.31	-13.49 (13.15)	-38.78, 11.80
Intercept	*(5, 3)*	0.05 (0.14)	-0.22, 0.30	0.26 (10.40)	-19.73, 20.25
14	*80*	-0.01 (0.09)	-0.19, 0.16	-1.22 (7.30)	-15.42, 12.99
Intercept	*(13, 67)*	-0.03 (0.04)	-0.11, 0.06	-4.81 (3.57)	-11.76, 2.14

Abbreviations: CI, confidence interval; SE, standard error.
[a] For the multilevel linear models, the outcome variables were centered around the concerning baseline sub-group means. We adjusted for gender (locked in the model) and clustered by calendar week. Weeks where either no baseline or no respective feedback message was available, were excluded.
[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.
[c] Total number of observations (number of participants having received the concerning feedback message, number of participants at baseline being compared to)
*** $p < .001$; ** $p < .01$; * $p < .05$ (after Benjamini-Hochberg correction)

Table 4. Linear models for the effects of different exposures to the UPcomplish intervention on QoL [a]

	Contextual performance			*Task performance*			*Perceived stress*		
FBM[b]	*n* [c]	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI
1 - 5	*49*	-0.26 (0.30)	-0.88, 0.35	*48*	-0.33 (0.27)	-0.87, 0.22	*48*	0.58 (2.89)	-5.24, 6.40
Int.	*(4, 45)*	-0.03 (0.09)	-0.20, 0.15	*(4, 44)*	-0.02 (0.08)	-0.18, 0.14	*(4, 44)*	-0.01 (0.83)	-1.69, 1.67
6 - 8	*101*	0.23 (0.14)	-0.05, 0.52	*100*	-0.06 (0.15)	-0.36, 0.24	*100*	0.40 (1.56)	-2.69, 3.50
Int.	*(19, 82)*	-0.02 (0.06)	-0.14, 0.10	*(19, 81)*	-0.02 (0.07)	-0.15, 0.11	*(19, 81)*	-0.06 (0.68)	-1.41, 1.29
9 - 11	*100*	0.09 (0.14)	-0.19, 0.36	*99*	0.05 (0.14)	-0.24, 0.33	*99*	-0.77 (1.54)	-3.83, 2.28
Int.	*(19, 81)*	-0.02 (0.06)	-0.14, 0.10	*(19, 80)*	-0.02 (0.06)	-0.15, 0.11	*(19, 80)*	-0.09 (0.67)	-1.43, 1.25
12 - 14	*79*	0.05 (0.16)	-0.28, 0.37	*78*	0.08 (0.16)	-0.23, 0.40	*78*	-1.49 (1.79)	-5.05, 2.07
Int.	*(15, 64)*	-0.02 (0.07)	-0.16, 0.12	*(15, 63)*	-0.02 (0.07)	-0.16, 0.12	*(15, 63)*	0.04 (0.78)	-1.52, 1.60
	Perceived pain (inverse)[d]			*Vitality*			*Emotional well-being*		
1 - 5	*47*	4.26 (12.09)	-20.09, 28.61	*47*	-2.04 (9.40)	-20.98, 16.90	*47*	-2.53 (6.47)	-15.57, 10.51
Int.	*(4, 43)*	-1.19 (3.53)	-8.29, 5.91	*(4, 43)*	-0.90 (2.74)	-6.43, 4.62	*(4, 43)*	-0.37 (1.89)	-4.17, 3.44
6 - 8	*99*	1.57 (5.51)	-9.36, 12.51	*99*	2.88 (4.92)	-6.88, 12.64	*99*	0.07 (3.53)	-6.92, 7.07
Int.	*(19, 80)*	-0.35 (2.41)	-5.14, 4.44	*(19, 80)*	-0.15 (2.15)	-4.42, 4.13	*(19, 80)*	-0.07 (1.54)	-3.14, 2.99
9 - 11	*97*	-0.04 (6.17)	-12.30, 12.21	*97*	6.28 (5.16)	-3.96, 16.51	*97*	3.97 (3.59)	-3.16, 11.10
Int.	*(18, 79)*	-0.57 (2.66)	-5.85, 4.71	*(18, 79)*	-0.48 (2.22)	-4.89, 3.93	*(18, 79)*	-0.04 (1.55)	-3.11, 3.03
12 - 14	*77*	11.90 (6.45)	-0.95, 24.76	*77*	9.79 (5.68)	-1.53, 21.11	*77*	4.26 (4.33)	-4.37, 12.90
Int.	*(15, 62)*	-0.92 (2.85)	-6.59, 4.76	*(15, 62)*	-0.60 (2.51)	-5.60, 4.39	*(15, 62)*	-0.19 (1.91)	-4.00, 3.62

Abbreviations: CI, confidence interval; SE, standard error.

[a] For the linear models, the outcome variables were centered around the baseline sub-group means. Due to singularity, the models were not clustered by calendar weeks. After backwards elimination, no covariates were included. Weeks where either no baseline or no respective feedback message was available, were excluded.

[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.

[c] Total number of observations (number of participants having received the concerning feedback message, number of participants at baseline being compared to)

[d] Perceived pain is inverted, i.e. higher numbers refers to not having any physical complaints.

*** $p < .001$; ** $p < .01$; * $p < .05$ (after Benjamini-Hochberg correction)

Effects of UPcomplish on psychosocial determinants

Participants having received FBMs number #6, #7, or #8 reported significantly lower perceived susceptibility (-0.66 [SE = 0.18; 95% CI = -1.03, -0.30; $p < .01$; $p_{corr} = .04$]) compared to baseline (Table 5). Within-subjects (Appendix D, Table 8) compared to baseline, after having received FBMs number #6, #7, or #8, they reported significantly lower perceived susceptibility (-0.75 [SE = 0.22; 95% CI = -1.18, -0.32; $p < .01$; $p_{corr} = .02$]), and after having received FBMs number #1 to #5, significantly higher intentions to reduce their SB (1.14 [SE = 0.27; 95% CI = 0.61, 1.66; $p < .01$; $p_{corr} = .02$]).

Post-hoc analyses

To analyze whether within-subjects' improvements (centered around calendar week means) in determinants, in SB, and in QoL were associated, we conducted pairwise Pearson correlations. Firstly, we report the correlations of the variables within the clusters (i.e. psychosocial determinants, SB variables, and QoL variables). Secondly, we report whether improvements in the psychosocial determinants were correlated with improvements in SB. Thirdly, we report whether improvements in the SB variables were associated with improvements in QoL. See Figure 4 for the correlations as well as univariate distributions of the variables. Improvement was calculated by subtracting the values at T0 from the values at T2 (survey variables), and by calculating week-to-week improvements (SB). Improvement refers to a beneficial development from worse values in the beginning (e.g. more perceived stress, more sitting, less performance) to better values in the end.

Table 5. Linear models for the effects of different exposures to the UPcomplish intervention on psychosocial determinants [a]

		Attitude		*Perceived social support*		*Perceived behavioral control*		*Perceived Susceptibility*		*Intention*	
FBM[b]	*n* [c]	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI
1 - 5	*49 (4, 45)*	0.11 (0.24)	-0.37, 0.58	0.29 (0.42)	-0.55, 1.12	-0.14 (0.33)	-0.81, 0.52	0.01 (0.37)	-0.73, 0.76	-0.18 (0.45)	-1.08, 0.72
Int.		-0.02 (0.07)	-0.16, 0.11	0.04 (0.12)	-0.20, 0.27	-0.03 (0.09)	-0.21, 0.16	-0.03 (0.11)	-0.24, 0.18	0.01 (0.13)	-0.24, 0.27
6 - 8	*101 (19, 82)*	0.00 (0.12)	-0.24, 0.24	-0.03 (0.22)	-0.47, 0.41	0.16 (0.16)	-0.16, 0.47	-0.66 (0.18)*	-1.03, -0.30	0.20 (0.23)	-0.26, 0.65
Int.		0.01 (0.05)	-0.09, 0.12	0.00 (0.1)	-0.19, 0.19	0.00 (0.07)	-0.14, 0.14	-0.03 (0.08)	-0.18, 0.13	0.04 (0.1)	-0.16, 0.23
9 - 11	*100 (19, 81)*	-0.04 (0.11)	-0.27, 0.19	0.05 (0.2)	-0.35, 0.45	-0.08 (0.16)	-0.39, 0.24	-0.30 (0.18)	-0.66, 0.07	-0.06 (0.21)	-0.47, 0.36
Int.		0.01 (0.05)	-0.09, 0.10	0.00 (0.09)	-0.17, 0.18	-0.01 (0.07)	-0.15, 0.13	-0.03 (0.08)	-0.19, 0.13	0.03 (0.09)	-0.15, 0.21
12 - 14	*79 (15, 64)*	0.09 (0.15)	-0.21, 0.39	0.13 (0.22)	-0.31, 0.58	0.08 (0.2)	-0.31, 0.47	-0.62 (0.26)	-1.14, -0.10	0.04 (0.26)	-0.48, 0.56
Int.		-0.01 (0.07)	-0.14, 0.12	0.05 (0.1)	-0.15, 0.24	-0.01 (0.09)	-0.18, 0.16	-0.03 (0.11)	-0.25, 0.20	0.03 (0.11)	-0.20, 0.25

Abbreviations: CI, confidence interval; SE, standard error.

[a] For the linear models, the outcome variables were centered around the baseline sub-group means. Due to singularity, the models were not clustered by calendar weeks. After backwards elimination, no covariates were included. Weeks where either no baseline or no respective feedback message was available, were excluded.

[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.

[c] Total number of observations (number of participants having received the concerning feedback message, number of participants at baseline being compared to)

*** p < .001; ** p < .01; * p < .05 (after Benjamini-Hochberg correction)

Correlations within psychosocial determinants, sedentary behavior, and quality of life improvements

Improvement in attitude was positively associated with improvement in perceived behavioral control (r = .46; 95% CI =.10, .71; p = .04; $p_{\text{corrected}}$ = .13) and intention (r = .39; 95% CI = .02, .67; p = .01; $p_{\text{corrected}}$ = .22). Improvements in SSSB and SB proportion were positively associated (r = .33; 95% CI = .09, .54; p < .01; $p_{\text{corrected}}$ = .12). Improvement in stress was positively associated with improvement in task performance (r = .44; 95% CI = .07, .70; p = .02; $p_{\text{corrected}}$ = .16), and emotional well-being (r = .52; 95% CI = .18, .75; p < .01; $p_{\text{corrected}}$ = .06), and improvement in vitality was positively associated with improvement in stress (r = .57; 95% CI = .25, .78; p < .01; $p_{\text{corrected}}$ = .02), pain (r = .44; 95% CI = .08, .70; p = .02; $p_{\text{corrected}}$ = .15), and emotional well-being (r = .64; 95% CI = .35, .82; p = $p_{\text{corrected}}$ < .001).

Correlations between improvements in psychosocial determinants and improvement in sedentary behavior

The improvements in psychosocial determinants and in SB were not associated.

Correlations between improvements in sedentary behavior and improvement in quality of life

Increased prolonged sitting (SSSB) was associated with improvements in vitality (r = .42; 95% CI = .05, .69; p = .03; $p_{\text{corrected}}$ = .16), which was likely due to on outlier (see Figure 4). None of the other QoL variables were associated with improvements in SB.

Discussion

This study investigated whether receiving UPcomplish FBMs had an effect on SB, QoL, and psychosocial determinants as compared to VitaBit only phases. Overall, the results suggest that neither on SB nor on QoL does the 12-week intervention have beneficial effects when compared to VitaBit only phases. When having received FBMs #6, #7, or #8, the participants felt less susceptible than at baseline, i.e. they agreed less that they should reduce their SB. When having received 5 or less FBMs, they indicated higher intentions to reduce and regularly interrupt their SB at work compared to their own baseline intention. None of the improvements in psychosocial determinants was associated with improvements in SB, and improvements in SB were not associated with improvements in QoL.

These results are in line with the evaluations of persuasion only interventions that did not reveal significant SB reductions (Direito, Carraça, Rawstorn, Whittaker, & Maddison, 2017; Stephenson et al., 2017), notwithstanding any publication bias (Reed et al., 2017). Although the relative distribution of the time spent sitting at baseline (64.3%) was similar to the distributions that were previously found among office workers (Clemes et al., 2014; Ryan et al., 2011), already 44% of the study population met the program goals that had been formulated for the intervention (Berninger et al., 2020). First, wearing a monitoring device and having received health information during the kick-offs might already have had positive effects (Barwais, Cuddihy, & Tomson, 2013; Gardner et al., 2016). Second, the voluntary participation might have resulted in a selection bias in such a way that only participants being already interested in a healthy lifestyle participated (Lauren Ashleigh Waters, Benedicte Galichet, Neville Owen, & Elizabeth Eakin, 2011). This was reflected by positive baseline attitudes towards reducing SB, high baseline QoL, and by the low response rate. Indeed, there seems to be a tendency that interventions with target groups showing more SB at baseline tend to have greater effects on SB compared to target groups with fewer SB (Stephenson et al., 2017). In the former, there is also more room for improvement. Post-hoc analyses within the scope of moderation analyses (in

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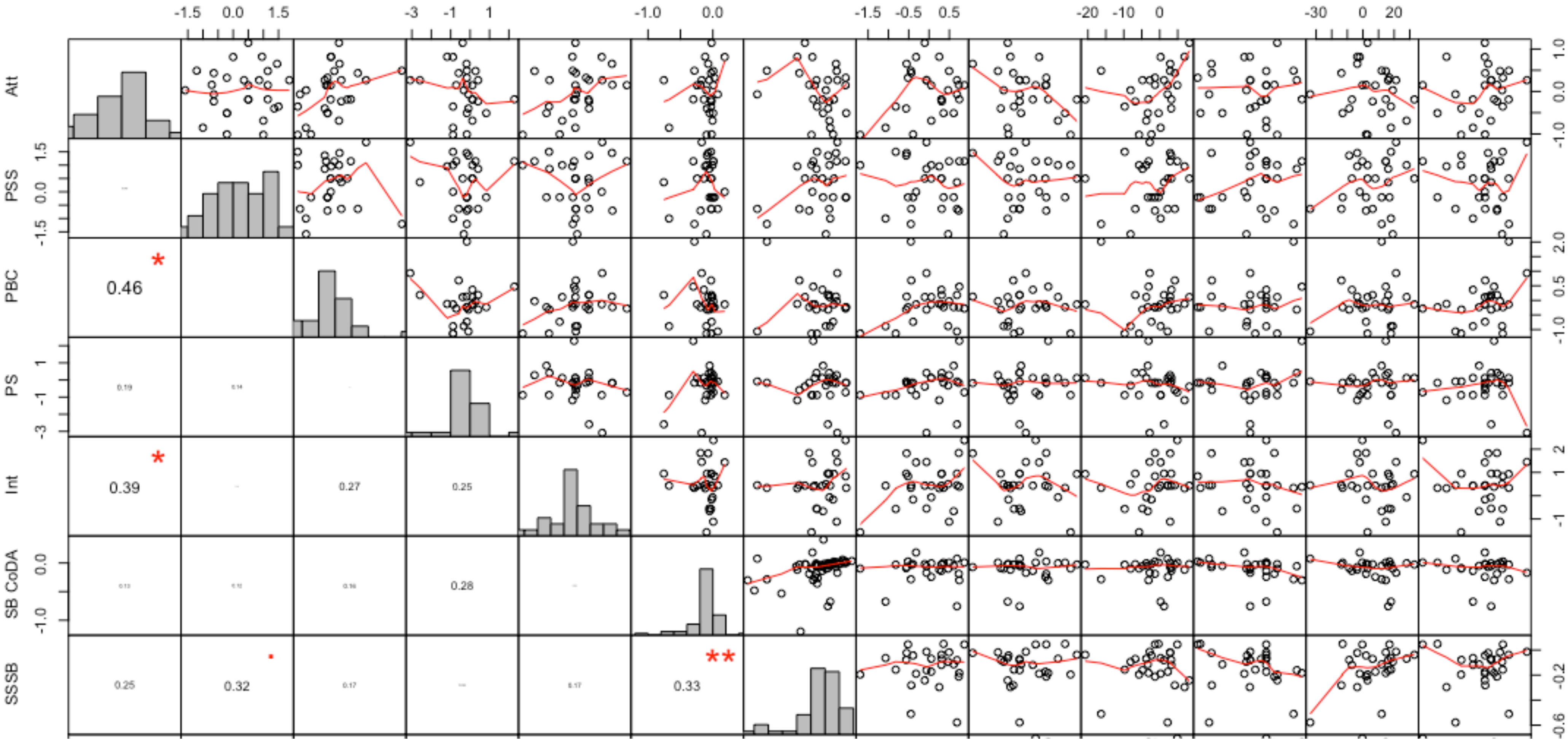

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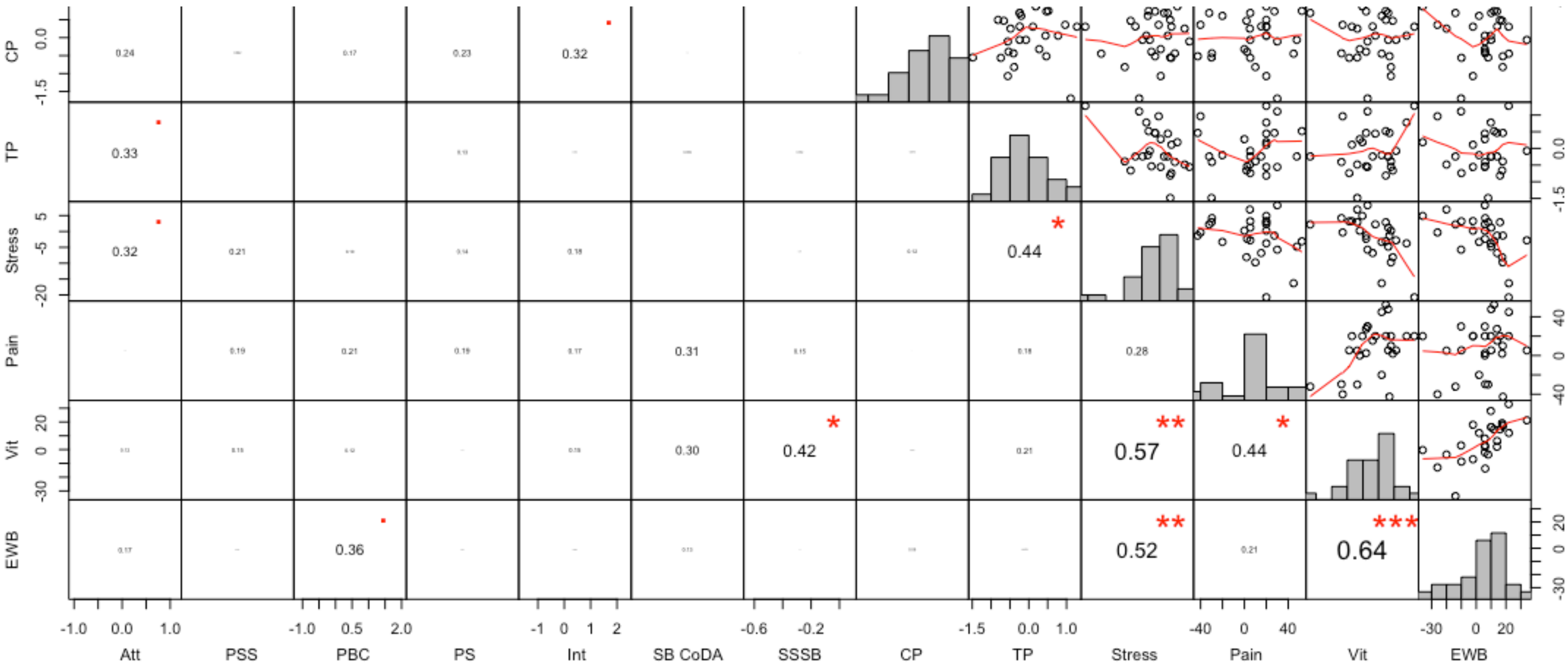

Figure 3. Pearson correlations and plots illustrating the linear and smoothed associations, respectively, between improvements in determinants (T2 – T0), SB (week to week), and QoL (T2 – T0).
Abbreviations: Att, attitude; PSS, perceived social support; PBC, perceived behavioral control; PS, perceived susceptibility; Int, intention; SB CoDA, SB proportion; SSSB, summed squared sitting bouts; CP, contextual performance; TP, task performance; Stress, perceived stress; Pain, not having any pain; Vit, perceived vitality; EWB, emotional well-being.

preparation) investigating differences between the participants with more and the ones with less baseline SB are therefore warranted (Bartholomew Eldredge et al., 2016; Berninger et al., 2020).

Several aspects might have impeded the effectiveness of the intervention. Firstly, while environmental changes such as standing desks have been found to be helpful when it comes to SB change (Gardner et al., 2016; Stephenson et al., 2017), the individual employee possesses limited possibilities to reduce sitting at work due to, for example, time constraints and the ways that work is structured (e.g. lengthy meetings at round-tables). Additionally, SB has become a habitual process because, in the Western society, it is linked to diverse contexts and activities, such as sitting during work (Conroy, Maher, Elavsky, Hyde, & Doerksen, 2013; Maher & Conroy, 2016). SB might therefore be less of a reasoned behavior and more determined by environmental, societal, or habitual factors. This is also reflected in the fact that none of the improvements in psychosocial determinants was associated with improvements in SB. Secondly, due to the high baseline QoL values and the selectivity of the sample (Lauren Ashleigh Waters et al., 2011), short-term effects of this intervention such as reductions of back-pain or an increase of vitality might not have been as dominant in order to serve as additional motivators (Segar, Guérin, Phillips, & Fortier, 2016), which was also reflected by the poor correlations between improvements in SB and QoL. Thirdly, the FBMs of this intervention merely focused on workplace SB. Since this constitutes the majority of the daily life, we had expected an overall reduction of SB. Nevertheless, while it might have had a reducing effect only on workplace sitting, leisure time habits (after working hours and weekends) might have mitigated the effects, which was already found in a similar intervention (De Cocker et al., 2016). Lastly, there seems to be a tendency that the intervention reduced SB after 6 to 8 FBMs, but the perceived need to sit less (i.e. perceived susceptibility) also drops around this moment. Thus, it might be helpful to have another personal meeting with the participants in the middle of the intervention, to keep sending two FBMs per week in the second half of the intervention, or to adapt the FBMs and the incentives themselves.

One of the strengths of the current study is that it examined the effects that a workplace SB intervention has on overall daily sitting. While many interventions only analyze the effects on workplace sitting, the study at hand focuses on the target group and their entire daily life providing better external validity and a more valid predictor for participants' general health. Furthermore, the analyses respected the compositional and thereby inter-dependent nature of physical behaviors, as well as included a novel, yet intuitive, operationalization of prolonged sitting. Additionally, the drop-out rates were smaller compared to other workplace physical activity and SB interventions, and they were mostly due to technical problems rather than a loss of motivation (Cajita, Kline, Burke, Bigini, & Imes, 2020). This is an indicator of the acceptability and, thereby, the potential of the UPcomplish intervention. Another strength of this study includes the application of a stepped-wedge design, which revealed more data points and reliability per participant, and allows for high external validity since data were collected throughout 75% of the calendar year.

The study also has some limitations. Firstly, we assume a recruitment bias among participants which might have resulted in a group of participants being dominated by females, being healthier and being more motivated than the average office employee. Nonetheless, baseline physical behavior proportions of participants are comparable to what was found in previous studies. Secondly, we included participants of diverse workplace sites which might not be comparable in terms of SB and the potential to reduce it. Nonetheless to increase internal and external validity, we centered all outcome variables around baseline company means, and included multiple company industries, education levels, team, and company sizes.

This study provides an essential addition to the literature on SB. Although UPcomplish was structurally developed using evidence from the literature and from theory, it was neither effective in improving SB nor QoL. In the middle of the intervention, participants perceived to be less susceptible to being sedentary. Firstly, we conclude that a workplace SB intervention might need to focus more on structural changes of the workplace environment since none of the determinants predicting reasoned actions were correlated with changes in SB. Secondly, workplace sitting might not only be influenced by the psychosocial determinants that were chosen for this intervention, but also by other psychosocial determinants or by different underlying beliefs. Lastly, the sample seemed to be selective in such a way that the participants were likely more motivated, less sedentary, and had higher QoL compared to the average office worker. It needs to be investigated whether UPcomplish was effective for certain subgroups, such as people being more sedentary.

Appendix *A*

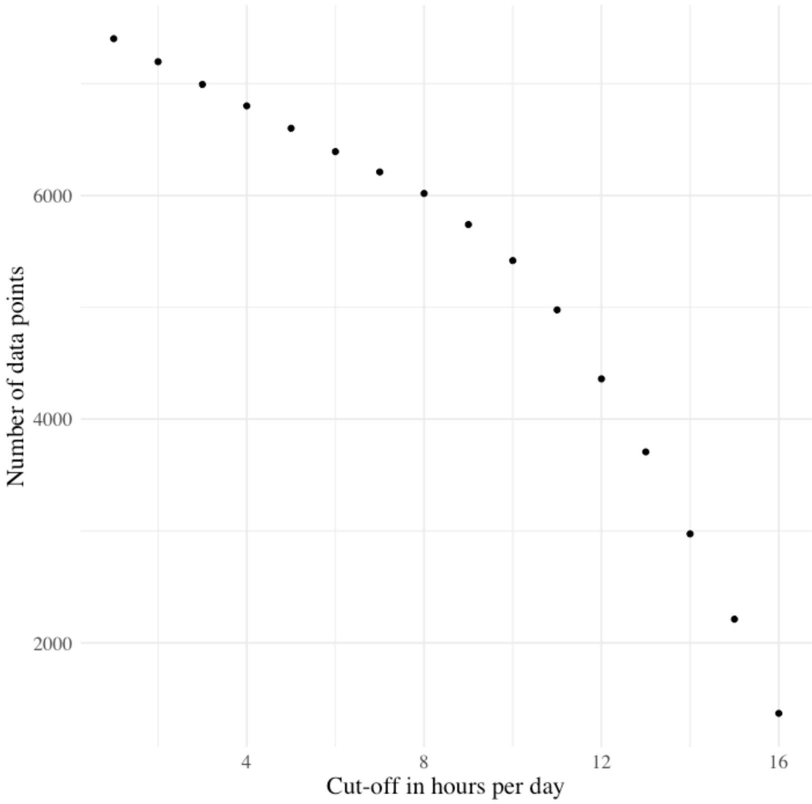

Figure 2. Number of days being retained by different daily wear time cut-off values in hours

Appendix B

Table 6. Multilevel linear models for the effects of different exposures to the UPcomplish intervention on SB parameters [a] (random intercept on the individual level)

		SB CoDA		*Summed Squared Sitting Bouts*	
Intervention [b]	n	β *(SE)*	95% CI	β *(SE)*	95% CI
1	236	-0.03 (0.03)	-0.10, 0.03	-0.06 (3.61)	-7.15, 7.06
Intercept		-0.01 (0.03)	-0.08, 0.06	0.52 (3.13)	-5.62, 6.65
2	224	0.01 (0.04)	-0.07, 0.08	-0.50 (3.68)	-7.74, 6.75
Intercept		-0.02 (0.04)	-0.09, 0.05	-0.87 (2.96)	-6.68, 4.94
3	197	0.24 (0.05)***	0.15, 0.33	20.83 (3.53)***	13.90, 27.78
Intercept		-0.01 (0.04)	-0.08, 0.07	-1.09 (2.95)	-6.87, 4.69
4	186	0.20 (0.05)***	0.11, 0.29	24.80 (4.56)***	15.84, 33.76
Intercept		-0.01 (0.04)	-0.08, 0.06	-0.49 (3.14)	-6.66, 5.67
5	129	0.05 (0.07)	-0.09, 0.18	2.37 (6.92)	-11.40, 15.94
Intercept		-0.01 (0.03)	-0.08, 0.05	-0.05 (2.75)	-5.44, 5.34
6	129	-0.08 (0.07)	-0.21, 0.06	-11.30 (6.38)	-23.79, 1.19
Intercept		-0.03 (0.04)	-0.10, 0.04	0.17 (3.02)	-5.76, 6.09
7	135	-0.08 (0.07)	-0.21, 0.05	0.03 (5.89)	-11.52, 11.58
Intercept		-0.01 (0.04)	-0.08, 0.07	1.55 (3.21)	-4.73, 7.84
8	113	0.04 (0.07)	-0.09, 0.17	4.82 (5.62)	-6.20, 16.06
Intercept		-0.02 (0.04)	-0.10, 0.06	0.69 (3.37)	-5.91, 7.30
9	105	0.05 (0.07)	-0.09, 0.19	-2.04 (6.04)	-13.94, 9.89
Intercept		-0.02 (0.05)	-0.12, 0.07	0.70 (3.89)	-6.93, 8.33
10	95	0.10 (0.07)	-0.05, 0.24	6.48 (6.26)	-5.80, 18.98
Intercept		-0.04 (0.06)	-0.15, 0.07	0.46 (4.49)	-8.34, 9.27
11	76	0.17 (0.08)	0.02, 0.33	9.62 (6.81)	-3.85, 23.13
Intercept		-0.05 (0.06)	-0.17, 0.06	-1.07 (4.81)	-10.51, 8.37
12	38	0.31 (0.13)	0.06, 0.57	19.97 (10.23)	-0.08, 40.19
Intercept		-0.03 (0.08)	-0.18, 0.12	-0.86 (5.79)	-12.19, 10.46
13	58	0.00 (0.1)	-0.21, 0.20	-29.37 (9.4)	-48.28, -10.02
Intercept		-0.03 (0.04)	-0.11, 0.06	1.08 (3.62)	-6.04, 8.21
14	53	-0.04 (0.1)	-0.24, 0.17	-12.33 (8.91)	-29.82, 5.45
Intercept		-0.07 (0.06)	-0.18, 0.04	0.13 (4.69)	-9.05, 9.32

Abbreviations: CI, confidence interval; SE, standard error.
[a] For the multilevel linear models, the outcome variables were centered around the baseline calendar week means. The models were clustered by individuals. After backwards elimination, no covariates were included.
[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.
*** $p < .001$; ** $p < .01$; * $p < .05$ (after Benjamini-Hochberg correction)

Appendix C

Table 7. Multilevel linear models for the effects of different exposures to the UPcomplish intervention on QoL (random intercept on the individual level) [a]

	Contextual performance			*Task performance*			*Perceived stress*		
Intervention [b]	*n*	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI
1 to 5	*16*	-0.34 (0.31)	-0.96, 0.27	*16*	-0.63 (0.42)	-1.45, 0.19	*16*	1.70 (2.98)	-4.13, 8.34
Intercept		0.04 (0.18)	-0.31, 0.38		-0.01 (0.21)	-0.42, 0.40		1.89 (1.84)	-1.75, 5.53
6 to 8	*57*	-0.02 (0.14)	-0.30, 0.26	*56*	-0.20 (0.15)	-0.51, 0.11	*56*	2.60 (1.56)	-0.61, 5.65
Intercept		-0.06 (0.1)	-0.26, 0.15		-0.07 (0.12)	-0.31, 0.16		-0.60 (1.09)	-2.74, 1.52
9 to 11	*58*	0.07 (0.12)	-0.15, 0.31	*58*	-0.07 (0.13)	-0.32, 0.19	*58*	-0.86 (1.02)	-2.88, 1.22
Intercept		-0.04 (0.08)	-0.20, 0.13		0.02 (0.09)	-0.15, 0.20		0.28 (1.07)	-1.85, 2.40
12 to 14	*45*	0.03 (0.15)	-0.28, 0.33	*45*	0.06 (0.16)	-0.28, 0.38	*45*	-2.31 (1.61)	-5.50, 1.00
Intercept		-0.11 (0.12)	-0.35, 0.13		-0.10 (0.12)	-0.34, 0.14		0.35 (1.2)	-2.02, 2.72
	Perceived pain (inverse) [c]			*Vitality*			*Emotional well-being*		
1 to 5	*16*	5.77 (12.05)	-17.80, 34.60	*16*	0.51 (6.66)	-13.31, 14.31	*16*	1.76 (6.27)	-14.29, 14.23
Intercept		-13.56 (7.02)	-27.38, 0.26		-6.91 (4.87)	-16.61, 2.79		-6.86 (3.65)	-14.06, 0.33
6 to 8	*56*	2.65 (5.31)	-7.78, 13.49	*56*	-5.51 (3.8)	-12.96, 2.38	*56*	-4.06 (3.65)	-11.21, 3.52
Intercept		4.38 (3.51)	-2.50, 11.27		2.43 (3.03)	-3.53, 8.42		0.99 (2.49)	-3.90, 5.89
9 to 11	*57*	-0.90 (5.85)	-12.61, 10.64	*57*	6.53 (2.79)	0.92, 12.08	*57*	2.53 (2.56)	-2.58, 7.64
Intercept		-0.16 (4.21)	-8.44, 8.12		-0.93 (3.23)	-7.31, 5.45		0.33 (2.25)	-4.11, 4.77
12 to 14	*45*	10.68 (5.47)	-0.05, 21.97	*45*	7.82 (4.62)	-1.43, 17.21	*45*	5.70 (3.85)	-2.09, 13.37
Intercept		6.40 (3.83)	-1.12, 13.92		-0.01 (3.61)	-7.14, 7.12		-0.26 (2.95)	-6.07, 5.56

Abbreviations: CI, confidence interval; SE, standard error.
[a] For the multilevel linear models, the outcome variables were centered around the baseline calendar week means. The models were clustered by individuals. After backwards elimination, no covariates were included.
[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.
[c] Perceived pain is inverted, i.e. higher numbers refers to not having any physical complaints.
*** $p < .001$; ** $p < .01$; * $p < .05$ (after Benjamini-Hochberg correction)

Appendix D

Table 8. Multilevel linear models for the effects of different exposures to the UPcomplish intervention on psychosocial determinants (random intercept on the individual level) [a]

		Attitude		*Perceived social support*		*Perceived behavioral control*		*Perceived Susceptibility*		*Intention*	
Intervention [b]	*n*	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI
1 to 5	*16*	0.81 (0.24)	0.32, 1.33	1.30 (0.43)	0.45, 2.20	0.49 (0.19)	0.10, 0.89	-0.16 (0.28)	-0.74, 0.47	1.14 (0.27)*	0.61, 1.66
Intercept		-0.13 (0.17)	-0.46, 0.20	0.32 (0.3)	-0.28, 0.91	-0.27 (0.18)	-0.64, 0.11	-0.30 (0.24)	-0.79, 0.19	-0.09 (0.13)	-0.35, 0.17
6 to 8	*57*	0.17 (0.13)	-0.08, 0.43	0.25 (0.22)	-0.18, 0.68	0.17 (0.16)	-0.16, 0.49	-0.75 (0.22)*	-1.18, -0.32	0.42 (0.24)	-0.06, 0.90
Intercept		-0.07 (0.1)	-0.25, 0.12	0.02 (0.14)	-0.25, 0.30	-0.02 (0.12)	-0.26, 0.21	-0.03 (0.13)	-0.28, 0.22	0.02 (0.17)	-0.32, 0.36
9 to 11	*58*	0.08 (0.13)	-0.17, 0.36	0.59 (0.2)	0.20, 0.99	-0.05 (0.12)	-0.28, 0.18	-0.44 (0.18)	-0.80, -0.09	0.29 (0.22)	-0.17, 0.73
Intercept		-0.01 (0.08)	-0.18, 0.15	-0.04 (0.11)	-0.27, 0.18	0.01 (0.1)	-0.18, 0.20	0.05 (0.13)	-0.20, 0.30	0.12 (0.14)	-0.15, 0.38
12 to 14	*45*	-0.11 (0.14)	-0.38, 0.16	0.34 (0.2)	-0.07, 0.74	-0.23 (0.14)	-0.52, 0.05	-0.44 (0.24)	-0.91, 0.04	0.24 (0.23)	-0.22, 0.71
Intercept		0.06 (0.1)	-0.14, 0.26	-0.14 (0.16)	-0.46, 0.17	0.04 (0.12)	-0.21, 0.28	0.15 (0.15)	-0.14, 0.44	0.09 (0.17)	-0.25, 0.42

Abbreviations: CI, confidence interval; SE, standard error.

[a] For the multilevel linear models, the outcome variables were centered around the baseline calendar week means. The models were clustered by individuals. After backwards elimination, no covariates were included.

[b] Feedback message is operationalized as having received this feedback message (and not more or less), which is compared to the baseline measurement of not having received any feedback.

*** $p < .001$; ** $p < .01$; * $p < .05$ (after Benjamini-Hochberg correction)

CHAPTER 7

Moderators of the effectiveness of UPcomplish on sedentary behavior, quality of life, and psychosocial determinants: A stepped-wedge design

Berninger, N. M., Crutzen, R., Ruiter, R. A. C., Kok, G., Plasqui, G., & ten Hoor, G. A. (2020). Moderators of the effectiveness of UPcomplish on sedentary behavior, quality of life, and psychosocial determinants: A stepped-wedge design (Submitted for publication)

Abstract

Objectives. Sedentary behavior (SB) is negatively associated with cardiometabolic health and quality of life (QoL). In the earlier developed and evaluated 12-week UPcomplish intervention, the aim was to reduce SB among office workers. In this study, we explore potential moderators of effectiveness.

Methods. We applied a stepped-wedge design with five intervention groups starting with time-lags of seven weeks (n = 142, 96 females). Participants wore the VitaBit sensor to measure SB continuously and received surveys about QoL and psychosocial determinants at the beginning, middle, and end of the intervention. Using linear models, we regressed baseline participant characteristics and behavior onto intra-individual improvements (centered around calendar week-means) in determinants, SB, performance objectives, and QoL.

Results. Expectedly, those who scored high in baseline intention, task performance, stress, vitality, and emotional well-being improved less in these variables. Baseline stress (β = -0.05 [SE = 0.01; 95% CI = -0.08, -0.02; $p_{\text{corrected}}$ = .02]) and emotional well-being (β = 0.02 [SE = 0.01; 95% CI = 0.01, 0.03; $p_{\text{corrected}}$ = .02]) were negatively and positively associated, respectively, with improvement in contextual performance. Baseline attitude (β = -12.92 [SE = 3.93; 95% CI = -20.80, -5.04; $p_{\text{corrected}}$ = .02]) and perceived behavioral control (β = -9.27 [SE = 3.04; 95% CI = -15.37, -3.16; $p_{\text{corrected}}$ = .03]) were negatively associated with improvements in emotional well-being. Post-hoc analyses with a sub-group of participants low in these determinants and QoL revealed that improvements in perceived behavioral control was associated with improvements in SB, which was associated with improvement in task performance. The average of days per week having registered SB was associated with improvements in attitude and perceived social support.

Conclusions. Participants who score low in baseline determinants might profit from UPcomplish via an increase of perceived behavioral control. In combination with physical and cultural organizational changes, UPcomplish might have the potential to improve SB.

Introduction

In recent decades, there has been an exponential growth of office work in Western societies (Prince et al., 2019). Office work is dominated by sedentary activities (i.e. sitting, lying, or reclining activities with low energy expenditure (Tremblay, Aubert, et al., 2017)); employees were found to sit about 66% of their days (Clemes et al., 2014; Ryan et al., 2011). Chau and colleagues found that, compared to employees exhibiting more active jobs involving more walking and lifting, office workers have 35% increased mortality rates (Chau et al., 2015). A reason for this is that independently of leisure time exercise, sedentary behavior (SB) increases the risk for overweight (Chau et al., 2012) and cardio-metabolic diseases, such as diabetes type 2 and coronary heart disease (Biswas et al., 2015; Van Uffelen et al., 2010; Wilmot et al., 2012). Despite increasing numbers of interventions to reduce SB, there is mixed evidence on their effectiveness.

Although interventions that involved environmental restructuring, i.e. the implementation of standing or treadmill desks, or that involved personal coaching, have been found to be effective in reducing SB, they are cost-intense (Coffeng et al., 2014; Hutcheson et al., 2018; Kwak et al., 2010; McEachan et al., 2011). For a large-scale implementation, low-cost interventions are needed. However, current interventions that are low-cost and focus on persuasion only, show mixed effects (Commissaris et al., 2016; Wang et al., 2018). Therefore, we developed a low-cost alternative to personal coaching, UPcomplish, involving personal coaches who support their participants with automated content. During the coaching participants wear the VitaBit sensor (Berninger et al., 2018). The VitaBit toolkit includes the sensor, which is attached at the thigh to measure sitting, standing and activity, a mobile phone application for monitoring behavior, and a computer portal, where participants can set goals and arrange competitions with others. VitaBit also provides a coaching portal, where coaches, if they are authorized, can retrieve participants' physical behavior (i.e. SB and physical activity) data.

By employing Intervention Mapping (IM), we applied findings from behavioral change theories and from previous literature and conducted own preparatory work to systematically develop UPcomplish. The result of applying IM was a logic model of the intervention, of which an excerpt is shown in Figure 1. It depicts the causal mechanisms from the practical applications of the UPcomplish and VitaBit intervention to the behavioral outcome, i.e. reducing prolonged sitting. For example, tailored feedback on the achievement of sitting goals, combined with positive behavioral feedback, is assumed to change the psychosocial determinant attitude. One of the underlying attitudinal beliefs (~Change objectives) being targeted by this positive behavioral feedback is: “Indicate that the amount of resources (time, skills) that will need to be invested in order to perform certain strategies [being suggested to reduce sitting] will be worthwhile as it will lead to positive outcomes”. The logic model assumes that by changing this attitudinal belief, it will help them to reduce their prolonged sitting (Berninger et al., 2020).

UPcomplish is a data-driven, tailored motivational intervention involving the VitaBit toolkit that allows for self-monitoring of SB. We implemented the UPcomplish intervention among 15 workplace sites to investigate its effectiveness. For the effect evaluation, we had expected the intervention to be effective in reducing daily sitting proportion and prolonged sitting as well as in increasing quality of life (QoL; i.e. vitality, performance, and well-being). Yet, when compared to the VitaBit-only baseline measurement phases both between and within participants we did neither find significant reductions in SB nor significant increases in QoL for the UPcomplish intervention (Chapter 6). Possible reasons for this may be recruitment bias of the intervention population (e.g. only employees being motivated or scoring high in well-being volunteered), but also unexpected deviations from the logic model of change underlying the intervention (Figure 1). For example, in a post-hoc analyses of the effect evaluation, we found that improvements in the psychosocial determinants were not associated with improvements in SB, and improvements in SB were not associated with improvements in QoL. It might therefore be that either SB among office workers is less of a reasoned action than we assumed or that only certain subgroups of participants engaged more in the intervention, and profited from improvements in determinants, in SB, or in QoL. The intervention population

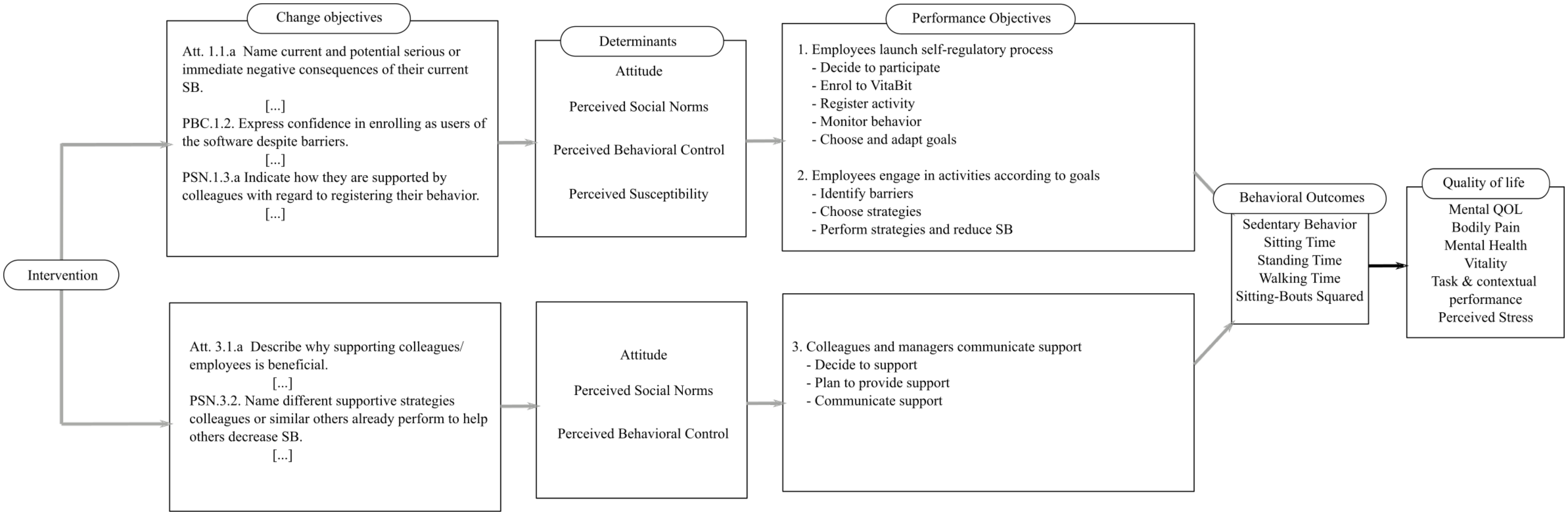

Figure 1. Illustration of the logic model of the UPcomplish and VitaBit intervention.

was dominated by females (68%), who reported high baseline QoL and psychosocial determinants. These and other baseline and participants' characteristics might have been factors that moderated the effectiveness of UPcomplish.

The purpose of the study at hand was to explore potential moderators of effectiveness for UPcomplish in terms of improvements in psychosocial determinants, in SB, and in QoL, as well as performance objectives (i.e. registering, monitoring, and engagement with coach). Firstly, participant characteristics such as gender, age, body mass index (BMI), or employment status are explored as moderators. Secondly, we assume that low baseline SB, high moderate-to-vigorous physical activity (MVPA), positive baseline determinants, and high baseline QoL (as a result of e.g. a selection bias) have resulted in lower potential for improvement and, therefore, less effectiveness of the intervention. Thirdly, the intervention messages might not have been accepted, read, or understood, which could have impeded the effectiveness. Instead of using a randomized control trial, the data were gathered using a stepped-wedge design with continuous recruitment. Therefore, we received annual spread data, avoided having a waiting control group, which is often associated with compliance issues, and increased statistical power (Hemming et al., 2015).

Methods

The study was pre-registered under: NL7503 (https://www.trial register.nl/trial/7503). The protocol of the intervention, with more details about the design has been published elsewhere (Berninger et al., 2020). Additional material, the raw data, and the R scripts are fully disclosed in the supplementary material (https://osf.io/qzp9m/?view_only=30ada8d6fc0e 4ac19a1610b8901f9f96). This manuscript adheres to the Consolidated Standards of Reporting Trials (CONSORT) checklist of information to include when reporting a stepped wedge cluster randomized trial (Hemming et al., 2018).

Study design and sample

We had five intervention groups including participants from 2 to 5 different sub-groups (i.e. companies). The intervention groups started with time lags of about 7 weeks, each receiving a kick-off meeting, before starting the baseline, VitaBit-only week, and the 12-week UPcomplish intervention. The eligibility criteria included that participants were able to walk and stand, that they were willing to download the VitaBit smartphone application, that they were office workers, and that they were able to speak and understand German.

VitaBit Software provided us with 200 devices, which we could use for the evaluation study (May 2019 - January 2020). With five intervention groups à 40 participants and an anticipated drop-out of 20% (32 participants per group, one group serving as both baseline and control), we conducted power calculations with an expected sample size of N = 192 and a Cohen's d estimate of 0.5. The population effect size would very likely (95%) be somewhere between 0.21 and 0.79, which we considered to be sufficiently accurate (Berninger et al., 2020). In order to recruit those 200 participants, we contacted German companies from multiple industries (e.g. public service, education, automotive). Of the 193 eligible participants who communicated interest in participating, 150 participants created a VitaBit account, and 142 wore their VitaBit at baseline. The flow of the participants in the intervention is shown in Figure 2: 45 participants wore the VitaBit device for 12 weeks or longer, whereas 38 participants collected less than 6 weeks of VitaBit data and were therefore excluded from the analyses of the current study. The number of participants that filled out the three surveys is illustrated in Figure 3: The baseline survey (T0) was filled out by 129 (91%), the mid evaluation survey (T1) by 67 (47%), and the end evaluation survey (T2) by 62 (44%) participants at T0, T1, and T2, respectively.

The participants could refuse their participation at all times, without giving a reason. The study and the consent procedure were approved by the Ethics Review Committee of the Faculty of Psychology and Neuroscience, Maastricht University, the Netherlands [ERCPN-188_11_02_20 18]. The trial was pre-registered in the Netherlands Trial Register under: NL7503.

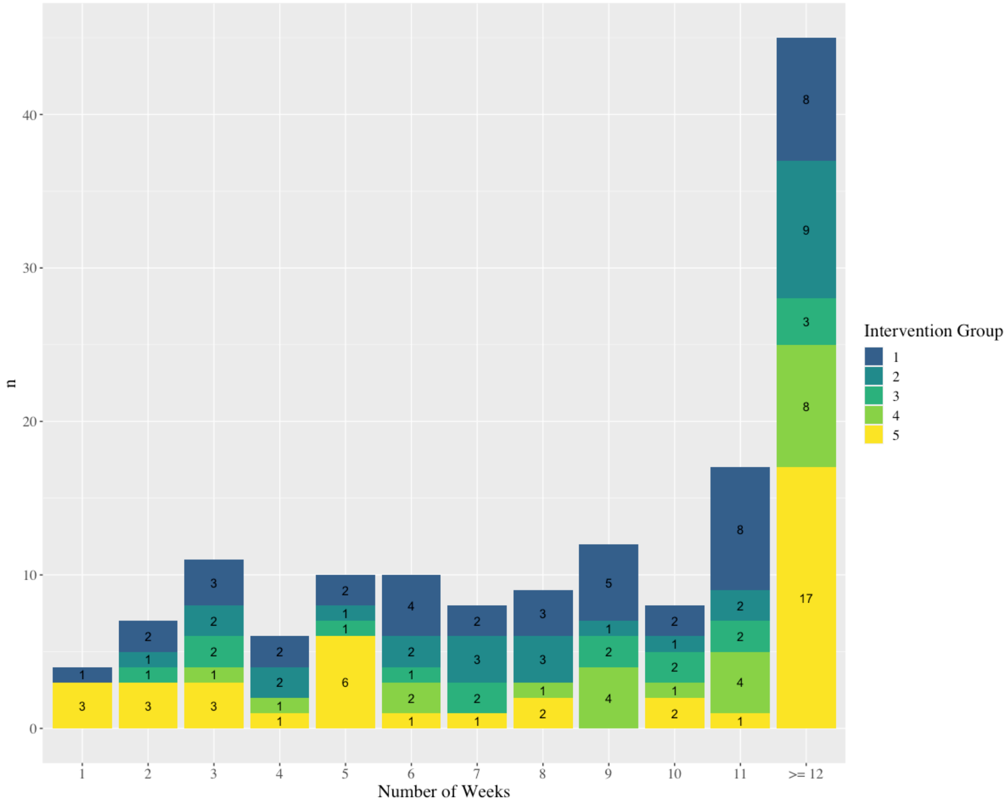

Figure 2. Number of participants per intervention group per number of weeks having collected VitaBit data

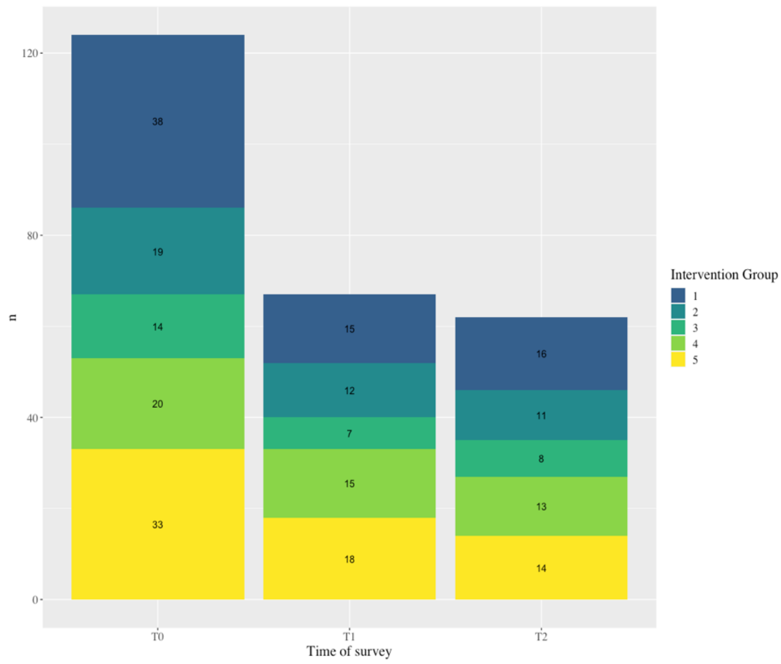

Figure 3. Number of participants that filled out the survey at baseline (T0), in the middle of the intervention (T1), and directly after the intervention (T2)

Procedure

Flyers with information about the study (incl. inclusion criteria, benefits to expect, and what to do) were distributed among German companies and potential participants (i.e. employees), who, if they were interested, further forwarded the flyers among their colleagues. If the management agreed, the employees could participate if they volunteered. Emails with an invitation to the personal kick-off meeting, instructions on how to create a VitaBit account, and the information sheet were sent to interested participants. The kick-offs, which took place in the companies of participants, took between 35 and 60 minutes, and included an introduction round, information about SB, the intervention, and the VitaBit toolkit. Additionally, participants could choose a sitting, standing, or activity goal, and they were supported to pair the VitaBit devices with the application on their smartphones. After written informed consent, participants started wearing the device and the baseline, VitaBit-only week, started, before participants received the intervention. Participants who were interested in participating, but unable to attend the personal kick-offs, received all the information per email. At baseline, in week 6, and directly after the intervention, participants received surveys on QoL and determinants. After the intervention, everyone received an individual and a group (i.e. company) report and a VitaBit voucher as a compensation for participation. The devices were collected earliest four weeks after the end of the intervention.

Intervention

The intervention consists of two components: the VitaBit toolkit and UPcomplish. UPcomplish serves as motivational support and includes 14 feedback messages that are sent to participants via their preferred channel (e.g. WhatsApp, email). The 14 feedback messages are tailored depending on the individuals' physical behavior data, personal goals, and to their individual hurdles. Twice and, as of week 6, once per week, participants received either a feedback message, a reminder (if they forgot to wear their VitaBit device), or nothing (if they were on a holiday or if they dropped out). In the latter two cases, the upcoming feedback messages were delivered delayed. The last two feedback messages were not delayed and delivered to all participants having data at the concerning point in time, because they were about competing each other and about how to keep the new habits that they acquired. The feedback messages included support in goal setting, goal-adjustment, in breaking down the goal to graded sub-goals, and feedback about the goals. Additionally, they included feedback about SB patterns (e.g. *"On Tuesday afternoon, your sitting periods seem to be specifically long"*). After being asked about their hurdles to sit less, the participants received tailored advice on how to overcome their hurdles. Every two weeks, they received activity challenges, such as not using the toilet on the same floor. In the end, the coach gave tips on how to sustain the new habits.

Measures

Figure 4 shows the measurements that were implemented during data collection.

Continuous measurements

Behavioral outcomes

The VitaBit device (3.9 × 1.4 × 0.9 cm, 4.8 g) measured physical behaviors (Atkin et al., 2012). The sensor was magnetically attached to clothing fabric at the thigh or placed in trouser pockets. It samples data with a rate of 33 Hz and an output rate of 30 seconds, which are stored on the device for at least 30 days. The data on the device are synchronized via Bluetooth Low Energy with the VitaBit smartphone application, before being delivered via mobile Internet to the back-end server. The data are stored in a time series database in a pseudonymized way, where they can be downloaded authorized persons. In a validation study, the device showed sensitivity of 85.7% and specificity of 91.2% for sitting (Berninger et al., 2018). The raw data are in a long format csv file (i.e., each row representing 30 seconds of a person) and include a user identifier, a time stamp, and three columns for sitting, standing, and activity.

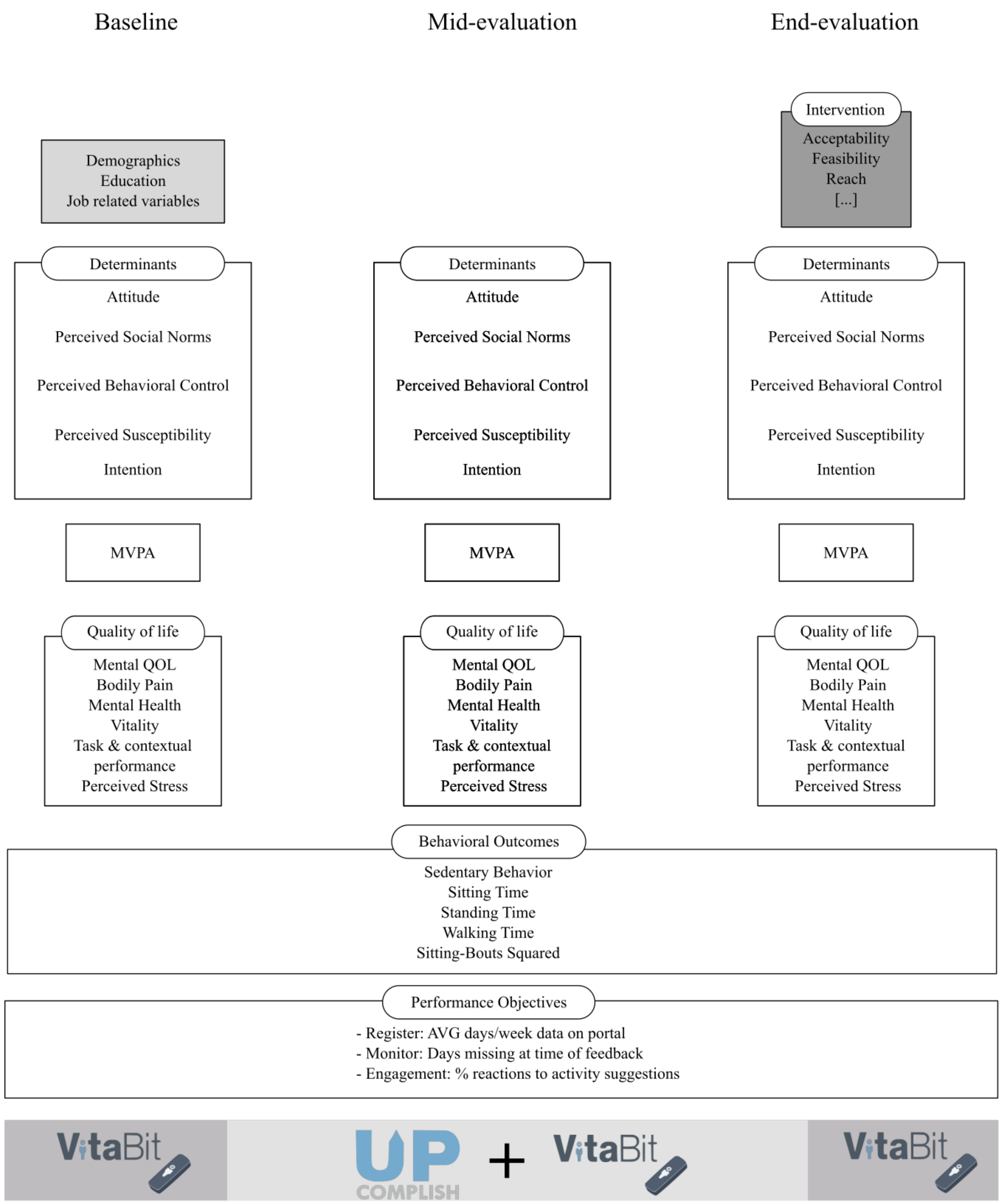

Figure 4. Overview of the measures that were conducted for the evaluation of UPcomplish. At baseline, in week 6, and in the end, surveys on determinants, moderate-to-vigorous physical activity (MVPA), and quality of life were distributed. Physical behaviors (i.e., behavioral outcomes) were continuously measured with the VitaBit. VitaBit data also provided information on performance objectives; for example, how often participants wore the device (i.e. registered behavior) and opened the app to synchronize their data (i.e. monitored behavior).

Performance objectives

The performance objectives were assessed via objective behavioral data. The days per week that participants had VitaBit data provided information on the registration of their SB. Behavioral monitoring was assessed simultaneously at the weekly feedback moments: The amount of days that were missing at the time of the feedback were used as a proxy because it gave an estimate on how often the app was opened. Engagement in the coaching, such as action planning, the discovery of barriers, and the performance objectives on the interpersonal level were assessed through the proportion of responses to coaching messages.

Online surveys

We distributed an online survey at baseline (T0), in week 6 (T1), and directly after the intervention (T2). All surveys included questions on psychosocial determinants and on QoL The survey at T0 additionally included sociodemographic and job-related variables, and the survey at T2 additionally asked about intervention characteristics. The English version of the Individual Work Performance Questionnaire was translated into German using back-translation (Brislin, 1970). We calculated Omegas (ω; > 2 items) and Pearson correlations (r; 2 items) to provide estimates for internal consistency (Crutzen & Peters, 2017; Revelle & Zinbarg, 2009).

Demographic, educational and job-related variables

Gender, age, educational level, height, weight, and job-related variables (e.g., team size) were obtained when the participants created their VitaBit account. They could choose between 8 different educational degrees (e.g., high school degree), between 29 different job titles (e.g., sales manager, administrative) and between 17 main company industries (e.g., educational, service). Additionally, in the online survey, they were asked about the usual number of workdays per week (1 item), about their employment status (full-time/part-time; 1 item) and received questions about sedentary job tasks (5 items). These could be phone calls, computer work, desk work, having meetings, and travelling/visiting clients, such as *"How much - on average per* *day (in %) - do you estimate you spend on* […] *Phone calls?"* (De Cocker et al., 2015).

Intervention acceptability

The questions on acceptability encompassed program related variables (e.g. understandability; 12 items; e.g., *"Do you agree with the following statements: […] The questions within the recommendations were clear"*), questions about the coach's advice (e.g. credibility; 7 items), and questions about behavioral maintenance (2 items) (De Cocker et al., 2015).

Psychosocial determinants

Participants were asked to indicate how much they agreed with specific statements on SB. These statements covered the determinants attitude (6 items; e.g. "[…] *walking around at work is healthy"*; ω = .62), perceived social support (2 items; e.g. "[…] *walking around at work is encouraged by my colleagues"*; r = .62), perceived behavioral control (4 items; e.g. *"I am sure that I can* […] *walk around at work, even though I feel bad, tired, tense or depressed"*; ω = .70), and intention (2 items; e.g. *"Are you planning to interrupt long sitting periods at work with* […] *walking breaks?"*; r = .43) (De Cocker et al., 2015). Perceived susceptibility to prolonged sitting was assessed with 2 items (e.g.*"My daily sitting time is more compared to what is recommended."*; r = .72) (Champion & Skinner, 2008; J. Kim & Park, 2012).

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Quality of life

The Individual Work Performance Questionnaire (seldom = 0 to always = 5) was used to assess task and contextual performance. Task performance (5 items; ω = .72) refers to the ability of performing the tasks that are essential, e.g. *"During the last week, I was able to perform my work well with minimal time and effort"*. Contextual performance (9 items; ω = .57) refers to the organizational, social, or psychological factors that are required for adequate functioning at work, e.g. *"I took on extra responsibilities."* (Koopmans et al., 2014). Furthermore, we used the Perceived Stress Scale (10 items; e.g. *"How often have you felt nervous and 'stressed'?"*; ω = .89) (S. Cohen et al., 1994; Klein et al., 2016) and the bodily pain (2 items; e.g. *"How much bodily pain* *have you had?"*; *r* = .85), emotional well-being (5 items; e.g. *"How much of the time have you been a happy person?"*; ω = .83), and vitality (4 items; e.g. *"How much of the time did you have a lot of energy?"*; ω = .86) sub-scales of the SF-36 (Ware Jr, 2000).

Moderate-to-vigorous physical activity

Since the VitaBit tool does not distinguish between different intensities of physical activity, we additionally assessed light and MVPA with the German version of the international physical activity questionnaire short form (max. 6 items; excluding SB; e.g. *"During the last 7 days, on how many days did you do vigorous physical activities like heavy lifting, digging, heavy construction, or climbing stairs as part of your work? Think about only those physical activities that you did for at least 10 minutes at a time."*) (Craig et al., 2003).

Data analyses

To clean and analyze the data, we used R version 4.0.2. We inspected the data using descriptive univariate analyses. We visualized them with histograms and QQ plots to check for normality. We reported normally distributed variables as means and standard deviations (SD), non-normally distributed variables as medians and Inter-Quartile-Ranges (IQR), and categorical variables as absolute numbers and percentages. SB was represented as proportion of the day by applying a compositional data approach (CoDA) (i.e. $z1_{sitting} = \sqrt{2/3}\ \ln\left(Sitting\%/\sqrt{Standing\%\ x\ Activity\%}\right)$) (Chastin, Palarea-Albaladejo, et al., 2015) and as sum of the squared sitting bouts (SSSB) ($SSSB = \sum_0^n SitBout_i^2$) [ref design paper]. We used only those days where a participant had collected at least 8 hours of physical behavior data (Toftager et al., 2013) and we excluded holidays from the analyses. We used the Mahalanobis distance method to detect outliers, which were then excluded from the analyses (Mahalanobis, 1936).

To calculate the within-subjects' improvements of SB, QoL, and psychosocial determinants, we only used calendar weeks, in which baseline data (of other participants still being in their baseline week) were available.

These baseline data were used to center the outcome variables in order to control for seasonal trends. The within-subjects' improvements of the variables (in %) that were collected with surveys were calculated as follows: if the survey was filled out 2 times, we subtracted the result from the second survey from the first survey (if lower values were better, such as in perceived stress, else, the first survey was subtracted from the second), which was then divided by the first survey. If the survey was filled out 3 times, additionally, the same calculation was performed with survey 2 and 3, before the improvement was averaged resulting in a survey-to-survey improvement. For SB, we took the averages for calendar weeks and calculated the week-to-week improvements.

Linear regression models were used with ordinary least squares, if residuals were normally distributed, else with percentage least squares (Tofallis, 2009), to explore potential moderators of effectiveness. Thereby, participant characteristics (e.g. gender, age, company industry, BMI), baseline physical behaviors (e.g. SB, MVPA), baseline QoL (e.g. perceived stress, vitality), and intervention perception (e.g. understandability, acceptability of the intervention) were regressed on within-subjects' improvements (centered around calendar week means) in psychosocial determinants (e.g. attitude, perceived social norms), on performance objectives (e.g. registering, monitoring), on improvements in SB, and in QoL. Due to potential ceiling effects, additional post-hoc analyses with a sub-group of participants were done. For testing statistical significance (two-sided), we used an alpha of .05, which we corrected by the help of the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995; Benjamini & Yekutieli, 2001).

Results

Participant characteristics

Table 1 presents the descriptive characteristics of the sample at baseline. Among the participants who agreed to participate, 143 (47 males) participants with a median age of 42.0 (IQR = 21.5) years and a mean BMI of

23.4 (SD = 5.2) kg/m^2 created a VitaBit account. Males had a higher ($p < .01$) BMI (median = 25.6, IQR = 5.2) than females (median = 22.3, IQR = 5.1). Among the 129 participants that filled out the survey at baseline, 35 (24.5% of the total sample), 60 (42.0%), and 28 (19.6%) indicated that their work tasks encompassed mainly computer and desk work, computer work, and desk work, respectively. The majority had a full-time position (72.7%) and a usual work week of 5 workdays (79.0%).

The psychosocial determinants (range 1 to 5) regarding sitting ranged from a mean of 3.4 (SD = 0.9) for perceived social support to a median of 5.0 (IQR = 1.0) for perceived susceptibility. At baseline, the participants wore their VitaBit device on average for 823.4 (SD = 107.5) minutes per day, of which the device measured a median of 510.2 (IQR = 95.3) SB minutes, 199.6 (IQR = 102.8) standing minutes and 91.7 (IQR = 45.7) activity minutes. Females collected more ($p < .001$) standing time (median = 224.8, IQR = 129.7) than males (median = 161.3, IQR = 73.2), while males collected more ($p < .01$) activity time (median = 105.2, IQR = 37.8) than females (median = 83.9, IQR = 45.6). Performance at baseline was on average 3.3 (SD = 0.6) for task and 3.6 (SD = 0.6) for contextual performance (1 to 5). On average, perceived stress (0 = no stress, 40 = high stress) was 15.0 (SD = 10.0), perceived pain (0 = much pain, 100 = no pain) was 77.5 (SD = 32.5), and vitality and emotional well-being (both 0 = low, 100 = high) were 54.4 (SD = 18.8) and 76.0 (SD = 20.0), respectively.

Variables affecting improvements in psychosocial determinants

Table 2 presents the results of the regression models exploring moderators affecting improvements in psychosocial determinants. After Benjamini-Hochberg corrections, higher baseline intentions were associated with significantly less improvement in intention during participation in the intervention (β = -0.52 [SE = 0.14; 95% CI = -0.81, -0.23; $p_{corrected} = .02$]). None of the other determinants was affected by participant characteristics, job related variables, baseline behaviors or how the intervention messages were perceived (all ps > .05).

Table 1. Descriptive characteristics of participants at baseline

	Female (n = 97)	**Male** (n = 47)	**Total** (n = 143)
Participant characteristics			
Age (years), median (IQR)	41.0 (20.5)	44.0 (19.5)	42.0 (21.5)
Anthropometrics, mean (SD)			
Height (cm)	168.6 (6.9)	180.5 (6.7)	172.4 (8.8)
Weight (kg)	65.0 (13.0)	82.0 (16.0)	70.0 (22.5)
BMI (kg/m^2)	22.3 (5.1)	25.6 (4.8)	23.4 (5.2)
Job related variables			
Main work tasks, n (%[a])			
Computer & desk work	26 (26.8)	9 (19.1)	35 (24.5)
Computer work	37 (38.1)	23 (48.9)	60 (42.0)
Desk work	21 (21.6)	7 (14.9)	28 (19.6)
Work status, n (%[a])			
Full-time	65 (67.0)	39 (83.0)	104 (72.7)
Part-time	20 (20.6)	1 (2.1)	21 (14.7)
Workdays per week, n (%[a])			
4 workdays	7 (7.2)	2 (4.3)	9 (6.3)
5 workdays	76 (78.4)	37 (78.7)	113 (79.0)
6 workdays	0 (0.0)	3 (6.4)	3 (2.1)
Psychosocial determinants			
Attitude, median (IQR)	4.3 (0.8)	4.2 (0.5)	4.2 (0.7)
Perceived social support, mean (SD)	3.4 (0.9)	3.3 (0.9)	3.4 (0.9)
Perceived behavioral control, median (IQR)	4.0 (1.0)	4.0 (0.9)	4.0 (1.0)
Perceived susceptibility, median (IQR)	5.0 (1.0)	5.0 (1.0)	5.0 (1.0)
Intention, mean (SD)	3.5 (0.8)	3.7 (0.9)	3.6 (0.9)
Physical behavior[b]			
Wear time (min d^{-1}), mean (SD)	835.7 (102.0)	797.8 (115.2)	823.4 (107.5)
Sedentary (min d^{-1}), median (IQR)	504.4 (96.5)	522.3 (92.7)	510.2 (95.3)
Sedentary compositional geometric mean[c], log-ratio variances standing, walking	62.3 (0.3, 0.2)	67.7 (0.2, 0.2)	64.3 (0.3, 0.2)
Standing (min d^{-1}), median (IQR)	224.8 (129.7)	161.3 (73.2)	199.6 (102.8)
Standing compositional geometric mean[c], log-ratio variances sitting, walking	27.2 (0.3, 0.2)	19.4 (0.2, 0.1)	24.5 (0.3, 0.3)
Activity (min d^{-1}), median (IQR)	83.9 (45.6)	105.2 (37.8)	91.7 (45.7)
Activity compositional geometric mean[c], log-ratio variances sitting, standing	10.5 (0.2, 0.2)	12.9 (0.2, 0.1)	11.3 (0.2, 0.3)
Quality of life			
Task performance, mean (SD)	3.6 (0.5)	3.4 (0.7)	3.6 (0.6)
Contextual performance, mean (SD)	3.3 (0.6)	3.3 (0.6)	3.3 (0.6)
Perceived stress, mean (SD)	15.0 (9.5)	16.0 (10.0)	15.0 (10.0)
Perceived pain, mean (SD)	77.5 (32.5)	87.5 (32.5)	77.5 (32.5)
Vitality, mean (SD)	54.5 (18.2)	54.3 (20.3)	54.4 (18.8)
Emotional well-being, mean (SD)	72.0 (18.0)	80.0 (20.0)	76.0 (20.0)

Abbreviations: SD, standard deviation; IQR, interquartile range; min d^{-1}, minutes per day; % d^{-1}, proportion of the day.

[a] Proportion of the sample. If not all participants filled out the survey, the percentages do not add up to 100%.

[b] Estimates of physical behaviors are estimated via VitaBit accelerometry.

[c] The percentage of the day is the estimated proportion of wearing-minutes spent in each activity level.

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Table 2. Linear regression models for the effects of participant characteristics, baseline variables, and intervention perception on improvements in psychosocial determinants

		Improvement attitude		*Improvement PBC*		*Improvement PSS*		*Improvement PS*		*Improvement intention*	
	n	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI
Gender	56	-0.05 (0.18)	-0.41, 0.31	-0.08 (0.22)	-0.52, 0.37	-0.28 (0.25)	-0.78, 0.22	-0.32 (0.27)	-0.87, 0.23	-0.26 (0.26)	-0.78, 0.26
Age (years)	54	0 (0.01)	-0.02, 0.01	-0.01 (0.01)	-0.03, 0.01	0 (0.01)	-0.02, 0.02	0.01 (0.01)	-0.01, 0.04	0 (0.01)	-0.02, 0.02
BMI (kg/m^2)	42	0.02 (0.02)	-0.01, 0.06	0.01 (0.02)	-0.03, 0.05	-0.03 (0.02)	-0.08, 0.02	-0.02 (0.03)	-0.07, 0.04	0.05 (0.02)	0, 0.09
Work status	55	-0.07 (0.22)	-0.5, 0.37	0.12 (0.27)	-0.42, 0.66	-0.09 (0.31)	-0.71, 0.53	-0.67 (0.32)	-1.32, -0.03	-0.37 (0.31)	-0.99, 0.25
Computer work (%/day)	56	0 (0)	-0.01, 0.01	-0.01 (0.01)	-0.02, 0.01	0 (0.01)	-0.01, 0.01	0 (0.01)	-0.02, 0.01	-0.01 (0.01)	-0.02, 0.01
Desk work (%/day)	52	0 (0)	0, 0.01	0 (0)	-0.01, 0.01	0 (0)	-0.01, 0	0 (0)	-0.01, 0.01	0.01 (0)	0, 0.01
Meetings (%/day)	53	0 (0.01)	-0.02, 0.02	0.01 (0.02)	-0.02, 0.04	-0.01 (0.02)	-0.05, 0.02	-0.01 (0.02)	-0.05, 0.03	0.02 (0.02)	-0.01, 0.06
Phone calls (%/day)	56	0.02 (0.01)	0, 0.03	0.01 (0.01)	0, 0.03	-0.02 (0.01)	-0.04, 0	0.01 (0.01)	-0.01, 0.03	0 (0.01)	-0.02, 0.02
Travels/Customers (%/day)	32	0 (0.01)	-0.03, 0.03	-0.01 (0.02)	-0.05, 0.03	-0.01 (0.03)	-0.06, 0.04	0.03 (0.02)	-0.02, 0.08	0.02 (0.02)	-0.02, 0.07
Attitude	56	-0.29 (0.16)	-0.61, 0.03	-0.09 (0.21)	-0.51, 0.32	-0.09 (0.23)	-0.56, 0.38	0.02 (0.26)	-0.5, 0.53	-0.16 (0.24)	-0.65, 0.33
Perceived behavioral control	56	-0.09 (0.13)	-0.34, 0.16	-0.23 (0.15)	-0.54, 0.08	-0.12 (0.18)	-0.48, 0.23	0.07 (0.2)	-0.33, 0.46	-0.06 (0.19)	-0.43, 0.31
Perceived social support	56	0.06 (0.1)	-0.14, 0.26	0.06 (0.13)	-0.2, 0.31	**-0.4 (0.13)**	**-0.66, -0.13**	0.1 (0.16)	-0.22, 0.41	0.12 (0.15)	-0.17, 0.42
Perceived susceptibility	56	-0.01 (0.12)	-0.25, 0.23	-0.02 (0.15)	-0.32, 0.27	0.04 (0.17)	-0.3, 0.38	**-0.49 (0.17)**	**-0.84, -0.14**	0.06 (0.18)	-0.3, 0.41
Intention	56	0.01 (0.11)	-0.21, 0.22	0.02 (0.14)	-0.25, 0.29	-0.14 (0.15)	-0.45, 0.16	-0.28 (0.16)	-0.61, 0.05	**-0.52 (0.14)**	**-0.81, -0.23**
MVPA	49	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0
z1_SB	56	-0.07 (0.23)	-0.52, 0.38	0.12 (0.28)	-0.45, 0.68	0.19 (0.32)	-0.45, 0.83	-0.25 (0.35)	-0.95, 0.45	0.07 (0.33)	-0.6, 0.73
SSSB	56	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0
Task performance	55	-0.08 (0.13)	-0.35, 0.18	-0.16 (0.16)	-0.47, 0.15	0.02 (0.18)	-0.35, 0.39	-0.06 (0.21)	-0.48, 0.35	0 (0.2)	-0.39, 0.4
Contextual performance	56	-0.07 (0.16)	-0.39, 0.25	-0.17 (0.2)	-0.57, 0.22	-0.05 (0.22)	-0.5, 0.4	-0.07 (0.25)	-0.56, 0.42	-0.06 (0.23)	-0.53, 0.41
Perceived stress	56	0.01 (0.01)	-0.02, 0.04	0 (0.02)	-0.03, 0.04	0.03 (0.02)	-0.01, 0.07	0 (0.02)	-0.04, 0.05	0.02 (0.02)	-0.02, 0.07
Perceived pain	56	-0.01 (0)	-0.01, 0	-0.01 (0)	-0.01, 0	0.01 (0.01)	0, 0.02	-0.01 (0.01)	-0.02, 0	-0.01 (0.01)	-0.02, 0
Vitality	56	-0.01 (0)	-0.01, 0	0 (0.01)	-0.01, 0.01	-0.01 (0.01)	-0.02, 0	0.01 (0.01)	-0.01, 0.02	-0.01 (0.01)	-0.02, 0.01
Emotional well-being	56	-0.01 (0.01)	-0.02, 0	-0.01 (0.01)	-0.02, 0.01	-0.02 (0.01)	-0.04, 0	0 (0.01)	-0.02, 0.02	-0.01 (0.01)	-0.03, 0.01
Acceptability	42	0.12 (0.15)	-0.18, 0.42	-0.06 (0.17)	-0.4, 0.27	-0.11 (0.17)	-0.45, 0.24	0.19 (0.22)	-0.26, 0.64	0.37 (0.2)	-0.04, 0.78
Understandability	42	0 (0.18)	-0.37, 0.36	-0.12 (0.2)	-0.52, 0.29	-0.12 (0.21)	-0.54, 0.3	0.08 (0.27)	-0.47, 0.64	0.05 (0.26)	-0.47, 0.57
Message processing	42	-0.05 (0.09)	-0.24, 0.14	-0.05 (0.1)	-0.27, 0.16	0.06 (0.11)	-0.16, 0.28	0.14 (0.14)	-0.14, 0.42	-0.15 (0.13)	-0.42, 0.11

SE, standard error; IQR, interquartile range; min d^{-1}, minutes per day; % d^{-1}, proportion. Cohen's (1988) **$f^2 \geq 0.15$** (medium) and **$f^2 \geq 0.35$*** (large) effect sizes

Variables affecting the performance objectives

Table 3 presents the results of the regression models exploring moderators affecting performance objectives. None of the performance objectives were associated with participant characteristics, job related variables, baseline behaviors or how the intervention messages were perceived (all *p*s > .05).

Variables affecting improvements in sedentary behavior

Table 4 presents the results of the regression models exploring moderators affecting improvements SB. SB improvement was not found to be influenced by participant characteristics, job related variables, baseline behaviors or how the intervention messages were perceived (all *p*s > .05).

Variables affecting improvements in quality of life

After Benjamini-Hochberg correction, most of the variables representing QoL were influenced by their own baseline values (see Table 5). Higher baseline task performance was associated with less improvements in task performance (β = -0.45 [SE = 0.01; 95% CI = -0.65, -0.25; $p_{corrected}$ < .001]), higher baseline stress with more improvement in perceived stress (β = 0.41 [SE = 0.11; 95% CI = 0.18, 0.63; $p_{corrected}$ = .02]), higher baseline vitality with less improvement in vitality (β = -0.33 [SE = 0.10; 95% CI = -0.52, -0.14; $p_{corrected}$ = .02]), and higher baseline emotional well-being with less improvement in emotional well-being (β = -0.48 [SE = 0.15; 95% CI = -0.77, -0.19; $p_{corrected}$ = .02]). Furthermore, lower baseline stress (β = -0.05 [SE = 0.01; 95% CI = -0.08, -0.02; $p_{corrected}$ = .02]) and higher baseline emotional well-being (β = 0.02 [SE = 0.01; 95% CI = 0.01, 0.03; $p_{corrected}$ = .02]) were associated with more improvement in contextual performance. Finally, higher baseline attitude (β = -12.92 [SE = 3.93; 95% CI = -20.80, -5.04; $p_{corrected}$ = .02]) and perceived behavioral control (β = -9.27 [SE = 3.04; 95% CI = -15.37, -3.16; $p_{corrected}$ = .03]) were associated with less improvements in emotional well-being.

Table 3. Linear regression models for the effects of participant characteristics, baseline variables, and intervention perception on performance objectives

		Monitoring			*Registering*			*Engaging*	
	n	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI
Gender	139	0.06 (0.24)	-0.41, 0.52	142	0.13 (0.2)	-0.27, 0.53	131	0.39 (4.66)	-8.84, 9.62
Age (years)	132	-0.02 (0.01)	-0.04, 0	135	0.02 (0.01)	0.01, 0.04	124	0.37 (0.19)	-0.01, 0.75
BMI (kg/m^2)	106	0.02 (0.02)	-0.03, 0.07	108	0.01 (0.02)	-0.03, 0.05	99	-0.1 (0.46)	-1.01, 0.81
Work status	123	0.35 (0.3)	-0.25, 0.94	126	-0.67 (0.25)	-1.16, -0.18	119	1.26 (5.67)	-9.96, 12.49
Computer work (%/day)	124	0 (0.01)	-0.01, 0.02	127	-0.01 (0)	-0.02, 0	120	-0.08 (0.1)	-0.28, 0.13
Desk work (%/day)	117	0 (0)	-0.01, 0.01	120	-0.01 (0)	-0.01, 0	114	-0.09 (0.06)	-0.21, 0.04
Meetings (%/day)	118	-0.01 (0.01)	-0.03, 0.02	120	-0.03 (0.01)	-0.05, -0.01	114	0.09 (0.24)	-0.39, 0.57
Phone calls (%/day)	121	0.01 (0.01)	-0.01, 0.02	124	-0.01 (0.01)	-0.03, 0	117	0.04 (0.15)	-0.26, 0.34
Travels/Customers (%/day)	59	0 (0.02)	-0.03, 0.03	60	-0.01 (0.01)	-0.03, 0.02	55	-0.31 (0.27)	-0.85, 0.23
Attitude	124	-0.16 (0.23)	-0.62, 0.3	127	0.11 (0.2)	-0.28, 0.49	120	-5.6 (4.35)	-14.23, 3.02
Perceived behavioral control	124	-0.32 (0.17)	-0.65, 0.01	127	0.33 (0.14)	0.06, 0.6	120	-2.99 (3.18)	-9.29, 3.3
Perceived social support	124	0.11 (0.13)	-0.14, 0.37	127	0.02 (0.11)	-0.2, 0.23	120	-1.64 (2.43)	-6.44, 3.17
Perceived susceptibility	124	0.16 (0.15)	-0.14, 0.46	127	-0.09 (0.13)	-0.35, 0.16	120	-2.74 (2.89)	-8.47, 2.99
Intention	124	-0.11 (0.14)	-0.38, 0.16	127	0.19 (0.11)	-0.03, 0.42	120	0.76 (2.63)	-4.44, 5.97
MVPA	116	0 (0)	0, 0	119	0 (0)	0, 0	114	0 (0)	0, 0
z1_SB	139	0.63 (0.3)	0.03, 1.22	142	-0.45 (0.26)	-0.96, 0.07	131	-1.32 (6.18)	-13.54, 10.91
SSSB	139	0 (0)	0, 0	142	0 (0)	0, 0	131	0 (0)	0, 0
Task performance	123	0.04 (0.2)	-0.35, 0.43	123	-0.15 (0.16)	-0.47, 0.16	119	-0.79 (3.7)	-8.12, 6.53
Contextual performance	124	0.39 (0.2)	-0.01, 0.79	124	-0.07 (0.17)	-0.4, 0.27	120	-3.15 (3.88)	-10.84, 4.53
Perceived stress	124	0.05 (0.02)	0.01, 0.08	124	-0.01 (0.02)	-0.04, 0.02	120	-0.21 (0.36)	-0.93, 0.5
Perceived pain	122	-0.01 (0.01)	-0.02, 0	122	0.01 (0)	0, 0.01	118	0.09 (0.1)	-0.11, 0.28
Vitality	124	-0.01 (0.01)	-0.02, 0.01	124	0.01 (0.01)	0, 0.02	120	0.07 (0.12)	-0.16, 0.3
Emotional well-being	124	-0.02 (0.01)	-0.03, 0	124	0 (0.01)	-0.01, 0.02	120	0.04 (0.16)	-0.27, 0.35
Acceptability	62	-0.13 (0.23)	-0.59, 0.32	62	0.09 (0.17)	-0.24, 0.43	60	1.87 (3.64)	-5.43, 9.16
Understandability	62	0 (0.28)	-0.56, 0.56	62	-0.03 (0.21)	-0.44, 0.38	60	3.79 (4.3)	-4.81, 12.38
Message processing	62	-0.06 (0.15)	-0.36, 0.24	62	0.12 (0.11)	-0.1, 0.34	60	4.67 (2.28)	0.12, 9.22

Abbreviations: SE, standard error; IQR, interquartile range; min d^{-1}, minutes per day; % d-1, proportion of the day.
Cohen's (1988) **f^2 ≥ 0.15** (medium) and **f^2 ≥ 0.35*** (large) effect sizes

Table 4. Linear regression models for the effects of participant characteristics, baseline variables, and intervention perception on improvements in sedentary behavior

		SB CoDA			*SSSB*	
	n	β *(SE)*	95% CI	*n*	β *(SE)*	95% CI
Gender	116	-1.27 (3.48)	-8.17, 5.64	120	-55.49 (51.57)	-157.62, 46.63
Age (years)	109	-3.22 (8.67)	-20.47, 14.02	115	-4.34 (2.12)	-8.54, -0.15
BMI (kg/m^2)	87	-17.15 (103.2)	-221.68, 187.37	92	-6.33 (5.72)	-17.7, 5.04
Work status	112	-2.37 (1.89)	-6.11, 1.38	116	-2.85 (65.95)	-133.5, 127.8
Computer (%/day)	113	-0.58 (1.2)	-2.95, 1.8	117	-1.04 (1.2)	-3.41, 1.34
Desk work (%/day)	106	7.41 (4.24)	-1.01, 15.82	110	-0.63 (0.71)	-2.05, 0.78
Meetings (%/day)	107	-3.14 (2.66)	-8.41, 2.12	110	-5.36 (2.64)	-10.6, -0.13
Phone calls (%/day)	111	-12.47 (4.61)	-21.74, -3.21	114	-1.52 (1.7)	-4.89, 1.85
Travels/Customers (%/day)	53	45.5 (79.9)	-112.84, 203.83	54	-4.04 (2.77)	-9.6, 1.52
Attitude	113	65.64 (56.18)	-45.68, 176.96	117	62.24 (50.45)	-37.69, 162.17
PBC	113	92.38 (42.36)	8.44, 176.32	117	34.47 (36.07)	-36.98, 105.92
PSS	113	-20.89 (51.07)	-122.08, 80.3	117	25.52 (27.19)	-28.33, 79.37
Perceived susceptibility	113	54.69 (46.11)	-36.69, 146.06	117	11.76 (32.2)	-52.02, 75.53
Intention	113	0.03 (0.02)	-0.01, 0.07	117	-18.63 (28.31)	-74.71, 37.44
MVPA	106	-91.78 (104.16)	-298.11, 114.55	109	0.02 (0.01)	0, 0.04
z1_SB	116	-0.01 (0)	-0.02, 0	120	54.5 (65.23)	-74.68, 183.68
SSSB	116	-61.55 (65.96)	-192.29, 69.18	120	0 (0)	-0.01, 0
Task performance	110	38.31 (69.06)	-98.57, 175.18	113	18.64 (39.85)	-60.33, 97.61
Contextual performance	111	-4.05 (6.57)	-17.06, 8.96	114	-112.04 (42.48)	-196.21, -27.86
Perceived stress	111	2.29 (1.72)	-1.13, 5.71	114	1.22 (3.99)	-6.7, 9.13
Perceived pain	109	1.12 (2.14)	-3.12, 5.37	113	2.04 (1.06)	-0.06, 4.13
Vitality	111	3.1 (2.81)	-2.46, 8.66	114	-2.43 (1.28)	-4.96, 0.11
Emotional well-being	111	60.09 (74.85)	-89.85, 210.04	114	-1.39 (1.72)	-4.8, 2.03
Acceptability	58	114.61 (90.32)	-66.32, 295.55	58	22.72 (52.17)	-81.79, 127.24
Understandability	58	1.55 (48.09)	-94.78, 97.89	58	30.88 (61.51)	-92.34, 154.1
Message processing	58	-1.27 (3.48)	-8.17, 5.64	58	28.47 (33.33)	-38.31, 95.24

Abbreviations: SE, standard error; IQR, interquartile range; min d^{-1}, minutes per day; % d-1, proportion of the day.
Cohen's (1988) **f² ≥ 0.15** (medium) and **f² ≥ 0.35*** (large) effect sizes

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Table 5a. Linear regression models for the effects of participant characteristics, baseline variables, and intervention perception on improvements in quality of life

		Task performance		*Contextual performance*		*Perceived stress*	
	n	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI
Gender	56	-0.22 (0.16)	-0.54, 0.09	0.01 (0.19)	-0.38, 0.4	-1.44 (1.55)	-4.54, 1.66
Age (years)	54	0 (0.01)	-0.01, 0.01	0 (0.01)	-0.01, 0.02	0.05 (0.07)	-0.08, 0.19
BMI (kg/m^2)	42	-0.01 (0.02)	-0.04, 0.02	0.01 (0.02)	-0.02, 0.05	0.04 (0.13)	-0.23, 0.31
Work status	55	0.04 (0.19)	-0.35, 0.42	-0.24 (0.23)	-0.71, 0.23	0.58 (1.9)	-3.24, 4.39
Computer work	56	0 (0)	-0.01, 0	0 (0)	-0.01, 0.01	-0.01 (0.04)	-0.09, 0.07
Desk work	52	0 (0)	0, 0.01	0 (0)	-0.01, 0.01	0.05 (0.02)	0, 0.1
Meetings	53	0.01 (0.01)	-0.01, 0.03	0 (0.01)	-0.03, 0.02	**0.28 (0.1)**	**0.08, 0.48**
Phone calls	56	0.01 (0.01)	-0.01, 0.02	0 (0.01)	-0.02, 0.02	0.1 (0.06)	-0.02, 0.23
Travels/ Customers	32	0 (0.01)	-0.03, 0.02	-0.02 (0.02)	-0.05, 0.02	0.14 (0.13)	-0.13, 0.4
Attitude	56	-0.15 (0.15)	-0.45, 0.14	0.45 (0.17)	0.11, 0.79	-1.72 (1.42)	-4.57, 1.14
PBC	56	-0.13 (0.11)	-0.35, 0.1	0.33 (0.13)	0.07, 0.59	-2.76 (1.04)	-4.84, -0.68
PSS	56	-0.09 (0.09)	-0.27, 0.09	0.27 (0.1)	0.06, 0.47	-1.44 (0.86)	-3.16, 0.28
PS	56	0.15 (0.11)	-0.07, 0.37	0.08 (0.13)	-0.18, 0.34	-2.02 (1.01)	-4.04, 0
Intention	56	-0.04 (0.1)	-0.23, 0.15	-0.03 (0.12)	-0.26, 0.21	-0.94 (0.94)	-2.82, 0.94
MVPA	49	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0
z1_SB	56	-0.43 (0.2)	-0.83, -0.03	0.02 (0.25)	-0.47, 0.51	-4.96 (1.86)	-8.69, -1.24
SSSB	56	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0
TP	55	**-0.45 (0.1)***	-0.65, -0.25	0.23 (0.14)	-0.05, 0.51	-2.08 (1.04)	-4.15, 0
CP	56	-0.16 (0.15)	-0.46, 0.13	-0.1 (0.17)	-0.44, 0.25	-0.79 (1.38)	-3.56, 1.98
Perceived stress	56	0.01 (0.01)	-0.02, 0.03	**-0.05 (0.01)**	**-0.08, -0.02**	**0.41 (0.11)**	**0.18, 0.63**
Perceived pain	56	0 (0)	-0.01, 0.01	0 (0)	-0.01, 0	-0.07 (0.03)	-0.13, -0.01
Vitality	56	0 (0)	-0.01, 0.01	0 (0)	-0.01, 0.01	-0.01 (0.04)	-0.09, 0.06
EWB	56	0 (0.01)	-0.01, 0.01	**0.02 (0.01)**	**0.01, 0.03**	-0.13 (0.05)	-0.23, -0.03
Accept	42	-0.15 (0.12)	-0.4, 0.1	0.06 (0.14)	-0.23, 0.35	-0.15 (1.26)	-2.69, 2.39
Understand	42	-0.17 (0.15)	-0.47, 0.13	0.05 (0.17)	-0.3, 0.4	0.49 (1.52)	-2.59, 3.57
Message processing	42	0.04 (0.08)	-0.12, 0.21	-0.02 (0.09)	-0.2, 0.16	-0.06 (0.8)	-1.67, 1.55

Abbreviations: SE, standard error; IQR, interquartile range; min d^{-1}, minutes per day; % d^{-1}, proportion of the day.

Cohen's (1988) **$f^2 \geq 0.15$** (medium) and **$f^2 \geq 0.35$*** (large) effect sizes

Table 5b. Linear regression models for the effects of participant characteristics, baseline variables, and intervention perception on improvements in quality of life

		Pain		*Vitality*		*Emotional well-being*	
	n	β *(SE)*	95% CI	β *(SE)*	95% CI	β *(SE)*	95% CI
Gender	56	-13.25 (5.9)	-25.08, -1.42	0.24 (4.25)	-8.28, 8.76	-5.26 (4.59)	-14.47, 3.96
Age (years)	54	0.16 (0.26)	-0.35, 0.68	0.02 (0.16)	-0.3, 0.34	0.18 (0.19)	-0.21, 0.57
BMI (kg/m²)	42	0.46 (0.61)	-0.77, 1.68	0.32 (0.35)	-0.39, 1.04	-0.44 (0.4)	-1.25, 0.38
Work status	55	-3.47 (7.49)	-18.5, 11.56	-0.7 (5.18)	-11.09, 9.69	-6.25 (5.6)	-17.48, 4.99
Computer work	56	0.02 (0.15)	-0.28, 0.33	-0.15 (0.1)	-0.36, 0.06	-0.09 (0.11)	-0.32, 0.14
Desk work	52	0.14 (0.1)	-0.05, 0.34	-0.04 (0.07)	-0.17, 0.1	-0.07 (0.07)	-0.22, 0.07
Meetings	53	0.5 (0.43)	-0.37, 1.36	0.31 (0.29)	-0.27, 0.89	0.55 (0.29)	-0.03, 1.13
Phone calls	56	0.05 (0.25)	-0.46, 0.55	-0.28 (0.17)	-0.62, 0.06	0.14 (0.19)	-0.24, 0.52
Travels/ Customers	32	**-1.1 (0.52)**	**-2.17, -0.03**	0.39 (0.36)	-0.35, 1.12	0.22 (0.36)	-0.52, 0.96
Attitude	56	-6.89 (5.63)	-18.19, 4.41	-2.53 (3.92)	-10.39, 5.32	-12.92 (3.93)	-20.8, -5.04
PBC	56	-6.74 (4.27)	-15.31, 1.83	-6.49 (2.88)	-12.26, -0.72	**-9.27 (3.04)**	**-15.37, -3.16**
PSS	56	-1.06 (3.49)	-8.04, 5.93	-3.29 (2.36)	-8.03, 1.44	-4.01 (2.57)	-9.17, 1.15
PS	56	-2.29 (4.12)	-10.54, 5.96	2.81 (2.82)	-2.84, 8.46	-4.68 (3.05)	-10.79, 1.42
Intention	56	-0.89 (3.75)	-8.39, 6.62	-1.21 (2.58)	-6.38, 3.95	0.81 (2.82)	-4.84, 6.47
MVPA	49	0 (0)	-0.01, 0	0 (0)	0, 0	0 (0)	0, 0
z1_SB	56	-11.84 (7.65)	-27.18, 3.5	-0.1 (5.38)	-10.89, 10.7	-8.61 (5.77)	-20.19, 2.96
SSSB	56	0 (0)	0, 0	0 (0)	0, 0	0 (0)	0, 0
TP	55	-0.43 (4.47)	-9.38, 8.53	-3.73 (3.12)	-9.99, 2.52	-4.41 (3.34)	-11.11, 2.29
CP	56	-4.09 (5.46)	-15.03, 6.86	-1.83 (3.77)	-9.39, 5.73	-3.31 (4.11)	-11.55, 4.94
Perceived stress	56	0.5 (0.49)	-0.48, 1.48	0.46 (0.33)	-0.21, 1.13	0.83 (0.35)	0.12, 1.54
Perceived pain	56	-0.32 (0.12)	-0.56, -0.09	-0.12 (0.08)	-0.29, 0.05	-0.15 (0.09)	-0.34, 0.03
Vitality	56	0.09 (0.15)	-0.21, 0.4	**-0.33 (0.1)**	**-0.52, -0.14**	-0.11 (0.11)	-0.34, 0.12
EWB	56	-0.01 (0.21)	-0.44, 0.41	-0.26 (0.14)	-0.54, 0.02	-0.48 (0.15)	-0.77, -0.19
Accept	42	3.87 (4.7)	-5.63, 13.37	0.43 (3.61)	-6.87, 7.73	1 (3.66)	-6.4, 8.4
Understand	42	-4.94 (5.7)	-16.46, 6.58	3.09 (4.36)	-5.71, 11.9	-0.85 (4.45)	-9.84, 8.14
Message processing	42	-3.43 (2.95)	-9.39, 2.53	-2.26 (2.26)	-6.82, 2.31	1.56 (2.31)	-3.1, 6.22

Abbreviations: SE, standard error; IQR, interquartile range; min d^{-1}, minutes per day; % d-1, proportion of the day.
Cohen's (1988) **$f^2 \geq 0.15$** (medium) and **$f^2 \geq 0.35$*** (large) effect sizes

Post-hoc analyses: Can subjects scoring low on relevant determinants and quality of life profit?

Seven variables were found to be associated with the effectiveness of UPcomplish: high intention, attitude, and perceived behavioral control as well as high task performance, vitality, and emotional well-being and low stress at baseline were associated with less improvements in psychosocial determinants and QoL. Therefore, we performed post-hoc analyses to analyze whether among a sub-group of the participants scoring below the median of the majority (i.e. at least four) of these seven variables ($n = 51$), the UPcomplish intervention would have potential for effectiveness. Therefore, we calculated pairwise Pearson correlations between all variables of the 4 parts of the logic model of the intervention (i.e. psychosocial determinants, performance objectives, SB, and QoL). We first report the correlations of improvements in the variables within the four parts. Afterwards, we report the correlations of the variables that represent the causal steps of the logic model (e.g. correlations between improvements in psychosocial determinants and performance objectives). Figure 5 shows the correlations and the univariate distributions of the variables. A positive improvement can be interpreted as a beneficial intra-individual week-to-week (as in SB) or as a measurement-to-measurement (as in QoL) development. Week-to-week SB improvement was calculated as proportional improvement in %, measurement-to-measurement improvement of the survey variables was calculated as average absolute improvement. For this analysis, we did not center the variables around calendar week means, because of the lower number of participants and available baseline data in the concerning calendar weeks.

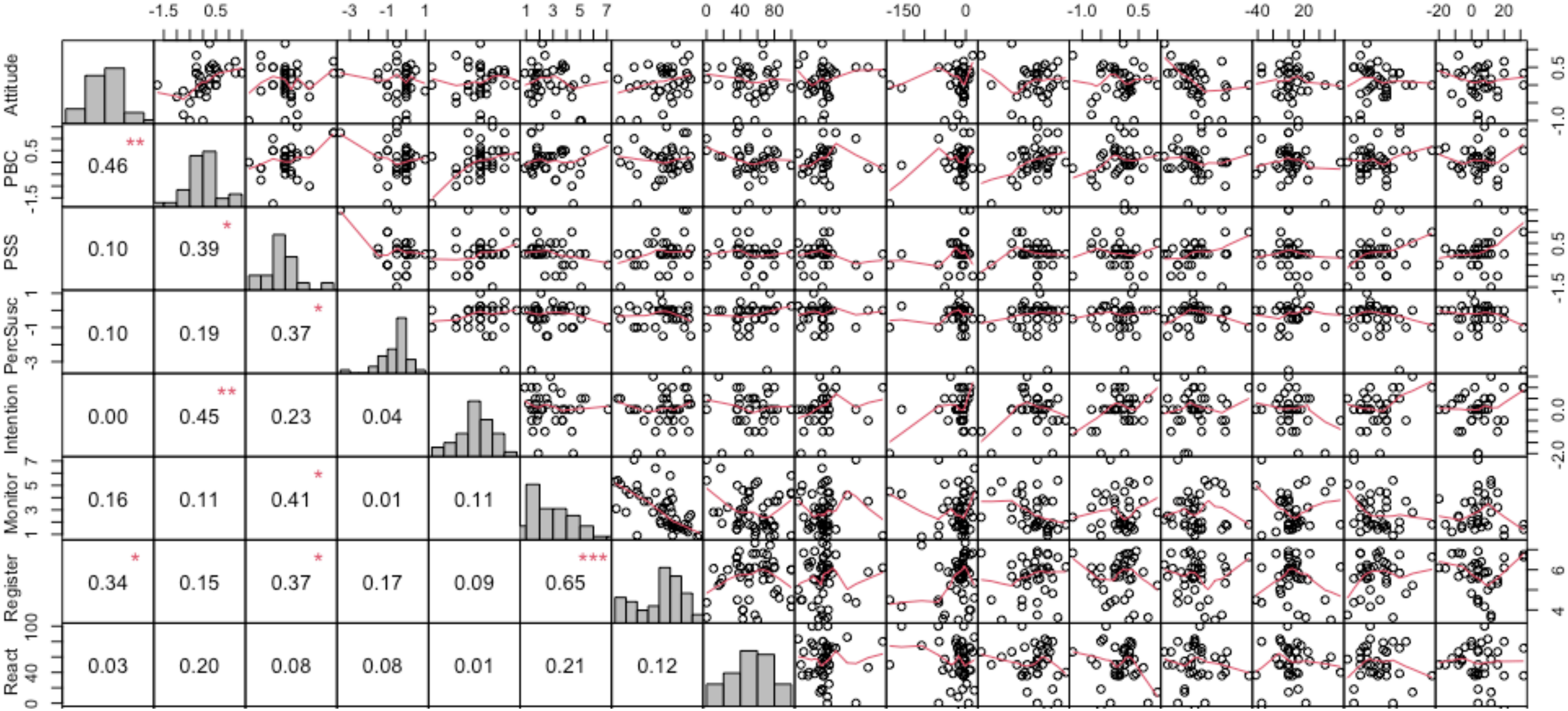
Correlations within the parts of the logic model of the intervention

Among the subgroup, improvement in perceived behavioral control was positively associated with improvement in attitude ($r = .46$; 95% CI = .15, .68; $p < .01$; $p_{corrected} = .03$) and in intention ($r = .45$; 95% CI = .14, .68; $p < .01$; $p_{corrected} = .04$), which was also found when analyzing all participants. Additionally, among the subgroup, perceived social support was positively associated with improvement in perceived behavioral control ($r = .39$; 95% CI

= .07, .64; p = .02; $p_{corrected}$ = .10) and negatively associated with increases in perceived susceptibility (r = -.37; 95% CI = -.63, -.05; p = .02; $p_{corrected}$ = .12). Average monitoring delay was negatively associated with registering sedentary behavior (r = -.65; 95% CI = -.78, -.45; p = $p_{corrected}$ < .001), which was also found for the entire group. Improvement in vitality was positively associated with improvement in emotional well-being (r = .59; 95% CI = .33, .77; p < .001; $p_{corrected}$ = .001), with improvement in contextual performance (r = .39; 95% CI = .08, .64; p = .02; $p_{corrected}$ = .09), and negatively with improvement in perceived stress (r = -.34; 95% CI = -.60, -.01; p = .04; $p_{corrected}$ = .16), but improvement in perceived stress was positively associated with improvement in emotional well-being (r = .58; 95% CI = -.76, -.30; p < .001; $p_{corrected}$ < .01). Improvements in task and contextual performance were positively associated (r = .34; 95% CI = .02, .60; p = .04; $p_{corrected}$ = .15). All associations within improvements in QoL were also found when analyzing all participants.

Correlations between the parts of the logic model of the intervention

Among the subgroup, improvement in attitude (r = .34; 95% CI = .01, .60; p = .04; $p_{corrected}$ = .16) and in perceived social support (r = .37; 95% CI = .05, .62; p = .03; $p_{corrected}$ = .12) were positively associated with how much participants registered their SB. Improvement in perceived social support was positively associated with how much participants monitored their behavior (r = .41; 95% CI = .09, .65; p = .01; $p_{corrected}$ = .07), which was also found in all participants. Improvement in perceived behavioral control was positively associated with improvement in prolonged SB (r = .34; 95% CI = .01, .60; p = .04; $p_{corrected}$ = .16), which was associated with improvement in task performance (r = .33; 95% CI = .01, .59; p = .05; $p_{corrected}$ = .16). Improvement in SB proportion was negatively associated with improvement in pain (r = -.37; 95% CI = -.63, -.04; p = .03; $p_{corrected}$ = .12).



Attitude
PBC
PSS
PercSusc
Intention
Monitor
Register
React
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0.10
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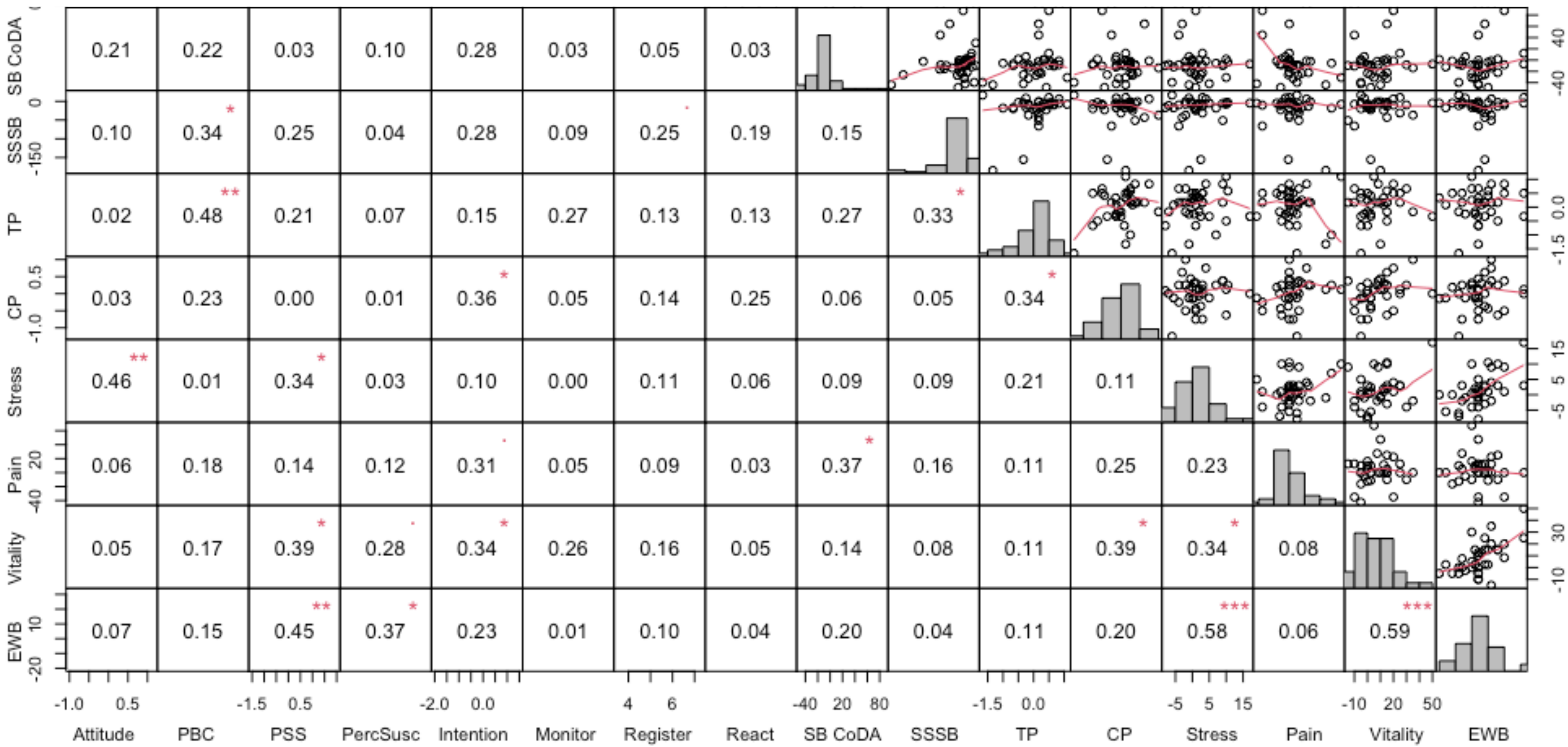

Figure 5. Pearson correlations and plots illustrating the linear and smoothed associations, respectively, between improvements in determinants (measurement-to-measurement), performance objectives, improvements in SB (week-to-week), and improvements in QoL (measurement-to-measurement). Abbreviations: PBC, perceived behavioral control; PSS, perceived social support; PercSusc, perceived susceptibility; SB CoDA, SB proportion; SSSB, summed squared sitting bouts; TP, task performance; CP, contextual performance; EWB, emotional well-being.
*** $r > .50$; ** $r > .40$; * $r > .30$

Discussion

The purpose of this study was to explore moderators of the effectiveness of the UPcomplish intervention, which had previously been found neither to have effects on SB, psychosocial determinants, nor on QoL (Chapter 6). Expectedly, we found that baseline psychosocial determinants and baseline QoL factors were negatively associated with improvements in determinants and QoL. Since baseline determinants and QoL were high among the participants of this study, we conducted a post-hoc analysis to investigate whether participants starting lower in determinants and QoL profited from the UPcomplish intervention. There was a tendency that among this subgroup, improvement in perceived behavioral control was associated with improvement in prolonged sitting, which itself was related to improvement in task performance.

We hypothesized that baseline characteristics of the sample such as psychosocial determinants, working tasks, or QoL would predict intra-individual improvements when receiving UPcomplish. Indeed and in line with previous research, we had a selective sample majorly including female participants (Robroek, van Lenthe, van Empelen, & Burdorf, 2009; Zigmont et al., 2018), and participants with high intentions to reduce their SB (Robroek, Lindeboom, & Burdorf, 2012). Additionally, the sample of the current study had higher baseline attitude, perceived behavioral control (i.e. self-efficacy) and perceived social support as opposed to a previous SB intervention study (De Cocker, De Bourdeaudhuij, Cardon, & Vandelanotte, 2017; Flint, Crank, Tew, & Till, 2017), as well as very high values in perceived susceptibility of too much sitting, which has also been found previously (Flint et al., 2017; Zigmont et al., 2018). These high values in psychosocial determinants are an indicator of the selectivity of the sample and might have impeded the potential for improvement, which could have been one of the reasons for the non-effectiveness of UPcomplish. However, although baseline intention was associated with lower improvement of intention, none of the other determinants were associated with improvements in SB, and, according to the post-hoc analysis, intention was not a factor being related to improvement in SB or to performance objectives such as monitoring behavior. This is in line with previous research that did not find psychosocial determinants to be mediators for improvements in SB (De Cocker et al., 2017).

SB might be less of a reasoned action but more a behavior that is determined by automaticity, and environmental conditions. Others already suggested that the challenge of reducing SB is rather the volitional process, which is bridging the gap between the intention and the actual behavior (Luszczynska, Schwarzer, Lippke, & Mazurkiewicz, 2011). Volition can be promoted (1) by action planning, which includes goal setting and the anticipation of barriers of behavioral change and (2) by perceived behavioral control, which elsewhere was already found to be a moderator in reducing workplace SB (De Cocker et al., 2017; Luszczynska et al., 2011). Similarly, in the post-hoc analyses, we found that among a sub-group of participants scoring lower in baseline determinants, improvement in perceived behavioral control was the only factor being related to improvement in SB. Although the UPcomplish intervention did include goal setting, the anticipation of barriers, and the increase of perceived behavioral control, the participants did not report an increase of perceived behavioral control (Chapter 6). However, at baseline the participants had a median of 4.0 out of 5.0 in perceived behavioral control, which might have been one of the core reasons for the lack of effectiveness. Therefore, the UPcomplish intervention might only be effective for participants scoring low in perceived behavioral control at baseline.

Except for perceived vitality, the sample of this study indicated to have good QoL, which could be due to a selectivity bias of the sample. However, there is no evidence that health affects participation in workplace health interventions (Robroek et al., 2012; Robroek et al., 2009). Hence, concerning QoL, the sample of this study might be representative of the working population in Germany. Additionally, although some aspects of QoL at baseline were associated with improvements in QoL during the intervention, they were likely be caused by ceiling effects because they did not relate to the performance objectives, or to improvements in psychosocial determinants and in SB (Bland & Altman, 1994). Only in the post-hoc analysis among a sub-group being lower in determinants and QoL than the average participant of this study, we found that improvement in physical pain was associated less reductions of SB. Similarly in another study, lower back pain at the beginning of the intervention predicted less improvement in sedentary behavior, which was assumed to be caused by a limited capacity of standing due to the perceived pain (Coenen et al., 2017).

Several steps of the implementation of the UPcomplish intervention might increase its effectiveness. Firstly, increasing the reach by also including employees being less motivated and self-efficacious at baseline, could improve its effectiveness considering the focus of UPcomplish being on psychosocial determinants. Albeit challenges of adoptions of workplace health programs (Sigblad, Savela, & Okenwa Emegwa, 2020), a structured development of an implementation program using Implementation Mapping might help to increase the reach of UPcomplish (Fernandez et al., 2019). For example, it would be important to increase awareness of the program, self-efficacy towards participation (e.g. to overcome time constraints and tiredness), and attitudes regarding the program among all potential participants already before they potentially adopt the program (Sigblad et al., 2020). Secondly, although the acceptability, understandability, and the message processing of the UPcomplish intervention were positive, more components need to be included to address other ecological levels (Bartholomew Eldredge et al., 2016; Robroek et al., 2009). Multi-component interventions have the potential for higher adoption rates due to an increased likelihood to match with the needs of participants (Robroek et al., 2009). Additionally, a workplace SB intervention including a psychosocial intervention, but also managers serving as role models, financial incentives to increase sustained participation, as well as environmental (e.g. standing desks) and cultural (e.g. walking around is seen as healthy and not as time-wasting) restructuring is likelier to be effective on the long run because it tackles both automatic and controlled motivational processes (Conroy et al., 2013; Flint et al., 2017; Quirk, Crank, Carter, Leahy, & Copeland, 2018). Lastly, although the UPcomplish intervention was systematically developed using the Intervention Mapping framework

(Berninger et al., 2020), the intervention content might have tackled the wrong psychosocial determinants (Kok et al., 2016). This should be investigated within the scope of a process evaluation implementing the intervention among participants with low baseline determinants.

This study has several strengths. First, we had longitudinal data of diverse company industries to our disposal that were collected during 75% of an entire year, and we additionally accounted for seasonal variations by centering the variables around calendar week means. A cheap and unobtrusive measurement tool with long battery life, the VitaBit device, facilitated the continuous collection of SB data. This increases external validity of the results. Second, we were the first to our knowledge that incorporated information of the entire logic model of a SB intervention, which provides interesting insights in the underlying mechanisms of reducing workplace SB. Third, we focused on the health effects for the target group, which was the reason to analyze daily SB and not merely workplace SB. Fourth, in order to represent SB, we applied both a compositional data approach to account for inter-dependencies of physical behaviors and a new value to represent prolonged SB. Lastly, UPcomplish was highly accepted among participants: the participants did not only indicate that they perceived the intervention positively also did they drop out late and mostly if they had technical problems rather than if they lost their motivation (Cajita et al., 2020).

One of the limitations of this study is that, since the psychosocial determinants and QoL were measured using self-reports, participants might have provided socially desirable answers (Krumpal, 2013). However, concerning QoL, using self-reports enabled the assessment of a large number of participants with lower timely and financial resources. Another limitation concerns the employees that did not adopt the intervention. Voluntary participation might have resulted in a selection bias, and our sample included mainly females, and participants scoring high in psychosocial determinants at baseline. However, we conducted a post-hoc analysis to investigate potential effects among a sub-group scoring lower in the psychosocial determinants. Lastly, in the post-hoc analysis, we could not center the variable around calendar week means because this would have resulted in fewer data, and therefore, less statistical power.

Especially high baseline values in, for example, intention were related to intra-individual improvement in the intention to sit less. However, this study showed that, except for perceived behavioral control, the psychosocial determinants (attitude, perceived social norms, perceived susceptibility, intention) do not seem to be important when reducing workplace sitting, and it might be more determined by the organizational environment and automatic behaviors. When promoting health at the workplace it is a challenge to reach a representative sample of employees including the ones being less interested in improving their health. Yet, this study showed, that probably especially these employees could profit most from a motivational intervention. It needs to be investigated whether UPcomplish could be effective in combination with changes in the physical and cultural environment of companies.

CHAPTER 8

General discussion

In this dissertation, the systematic development and evaluation of an intervention to reduce sedentary behavior among office workers is described. Initially, evidence from the literature, from theory, and from empirical research was used. Complementary, additional studies were conducted in order to refine the intervention components. Lastly, we evaluated our intervention to gather information on the effectiveness of the intervention and on underlying mechanisms of effectiveness. Despite the systematic and comprehensive development, and the high acceptability of the program, we did not find support for the intervention being effective in reducing overall sedentary behavior among a cohort of highly motivated office workers. However, during the intervention development we learned that 1) the VitaBit, a wearable activity monitor, shows acceptable sensitivity and specificity for sedentary behavior, 2) the algorithm representing complex sedentary behavior patterns is a more adequate tool to predict health compared to conventional methods, and 3) the intervention might be effective for employees low in perceived behavioral control. In this chapter, we further discuss the lessons learned during the development of the UPcomplish intervention, the outcome of the validation of the VitaBit device and the new algorithm including methodological considerations, as well as the results of the evaluations.

The problem with sedentary behavior

The prevalence of jobs majorly encompassing office work has risen from 15% in the 1960s to 20% in the 1990s (Church et al., 2011), and it is stabilizing in the last decade (Loyen et al., 2018). This is not problematic per se, but office workers spend on average two thirds of their working days in sedentary behaviors (Prince et al., 2019). Sedentary behavior has been linked to increased mortality rates, and amongst others risk for Diabetes Type II and coronary heart diseases (Carter et al., 2017; Patterson et al., 2018). Despite increasing awareness and attention to the observation that sedentary behavior is too prevalent in the Western society, evidence of successful interventions to reduce sedentarism is limited to expensive personal coaching or (also expensive) changes of companies' working equipment (e.g. standing desks, fitness center) (Commissaris et al., 2016; Hutcheson et al., 2018; Wang et al., 2018). Yet, it is not clear whether these expenditures yield a proper return on investment: the benefit of sedentary behavior programs in relation to the costs being involved. Therefore, the costs of the investment need to be reduced to a minimum, while increasing or at least keeping the benefit, which is the effectiveness of the intervention in reducing sedentary behavior and, on the long run, increasing health, quality of life, but also productivity and employability of office workers.

Ingredients of a successful intervention to reduce sedentary behavior

We propose three ingredients for a successful intervention to reduce sedentary behavior, namely a) a valid measurement tool, b) healthier behaviors as replacement of the undesired behavior, and c) the proper use of effective methods for behavior change.

A valid measurement tool

The origins of sedentary behavior research and interventions were based on self-reported sedentary behavior. Thereby, questionnaires, such as the International Physical Activity Questionnaire (Craig et al., 2003), were distributed (mostly multiple times) among the target group members before being analyzed and interpreted (Kwak et al., 2010; McEachan et al., 2011). Despite the possibility to distribute them among a large scale of people, self-reports of sedentary behavior come with several disadvantages. First, especially methods that require intensive and frequent self-monitoring constitute a burden to the participants and might, therefore, reduce compliance (Atkin et al., 2012). Second, as compared to objective methods, self-reports score lower in both test-retest reliability and validity (Foley, Maddison, Olds, & Ridley, 2012). Third, tailored interventions with individualized feedback would require a massive workload (data entry, cleaning and analysis) before a coach would be able to provide participants with feedback (Atkin et al., 2012). Nowadays, objective methods, such as accelerometry, are increasingly applied providing sedentary behavior researchers and coaches with continuous measurement tools that come with great psychometric properties (Plasqui, 2017; Plasqui et al., 2013). Yet, wearables that are thoroughly validated, such as the ActiGraph (ActiGraph LLC, Fort Walton Beach, FL, USA) or the activPAL (PAL Technologies Ltd., Glasgow, UK) require massive financial and timely resources (C. L. Edwardson et al., 2017; Heesch, Hill, Aguilar-Farias, van Uffelen, & Pavey, 2018). For example, high costs for the device and software licenses hinder large-scale implementation; they require profound skills in the analysis of big data; and multiple possibilities to define wear-time cut-off points, physical behavior (i.e. both sedentary behavior and physical activity) thresholds, and data output rates decrease comparability between studies (Atkin et al., 2012; C. L. Edwardson et al., 2017). VitaBit software developed a low-cost accelerometer with a firmware, which already converts the raw accelerations into the three physical behavioral categories sitting, standing, and walking. As soon as participants open the app, the data are automatically synchronized and sent to the server facilitating tailored feedback while the device is still in the tenure of participants. Hence, if the VitaBit tool validly distinguishes between sitting, standing, and physical activity, it would be the first ingredient to a successful sedentary behavior intervention.

Healthier replacement behaviors

Every day has 24 hours. Therefore, a reduction of sedentary behavior necessarily requires an increase in other behaviors, such as sleep, standing or physical activity. These physical behaviors are all interdependent and the day should be composed as healthy as possible (Chastin, Palarea-Albaladejo, et al., 2015). Additionally, some researchers found that prolonged sedentary behavior should be regularly interrupted (Dunstan et al., 2012; Healy et al., 2013). Therefore, if we aim for a reduction of sedentary behavior and shorter sitting bouts, we need to suggest alternatives. For example, in our intervention in order to facilitate an increase of walking bouts, we suggested to hold walking instead of sitting meetings, to drink more during working hours, and to use a washing room, which is not on the same floor as the office of the target group. For physical activity and sedentary behavior interventions, the physical behaviors should be balanced, i.e. sedentary behavior being minimized and replaced with other health behaviors, while the sedentary behavior bouts should be frequently interrupted. It is still questionable, how long these sitting interruptions should be and with which behaviors they should be interrupted (e.g. if is light physical activity sufficient or is it better to interrupt them with moderate physical activity). Others already found that regularly interrupting sitting with standing and light physical activity is at least equally beneficial compared to performing single bouts of moderate-to-vigorous physical activity if the behaviors yield the same energy expenditure (Duvivier et al., 2017).

Effective methods of behavior change

Behavior is majorly determined by cognitive processes: attitudes, norm perceptions and automatic, habitual tendencies are examples (Crutzen & Peters, 2018). Hence, in order to change behavior, relevant (i.e. important and changeable) psychosocial determinants inherent to the problem behavior need to be discovered and, with the help of effective behavior change methods, changed. The Intervention Mapping protocol is a framework guiding the process from assessing the problem behavior and its determinants to developing, implementing and evaluating a behavior change intervention (Bartholomew Eldredge et al., 2016). Here, each step of the intervention development requires careful research, for instance, to tackle the right problem behavior, the right psychosocial determinants, and to use the right behavior change methods (Ruiter & Crutzen, 2020). Literature and theories can help to support this development but are not always thorough or not transferrable to dissimilar target groups, needs or cultures. Moreover, it is important to consider the parameters of effectiveness, which are rules that need to be considered when translating methods of behavior change into practical applications. If these parameters are not respected, the practical applications will, very likely, not be effective in changing the determinants that they target (Crutzen & Peters, 2018; Kok et al., 2016).

The road to a potential solution

As outlined in this dissertation, we applied the Intervention Mapping protocol to systematically develop the UPcomplish intervention, which consists of automated, motivational feedback messages delivered by a personal coach, and it is based on the VitaBit measurement toolkit. We applied findings from previous sedentary behavior research and from behavior change theories (**Chapter 3**). After a validation study (**Chapter 2**), based on which we determined the VitaBit to be a suitable base for a sedentary behavior intervention, we continued with the development of UPcomplish. A few components of the first version of UPcomplish were designed, developed and pre-tested before being further refined (**Chapter 3**). After a pilot-test, which was conducted to implement the entire UPcomplish intervention, yet not automatized, among a small cohort of potential participants, we automatized the feedback messages and planned the methodology of the evaluation study. Moreover, re-occurring questions about details on recommended sedentary behavior patterns (e.g. “How long am I supposed to be standing? Can I sit longer when I went for a run in the morning?”) motivated us to develop an algorithm (SPORT), which would help us in the future to provide participants with clear answers (**Chapters 5**). Eventually, we implemented the UPcomplish intervention among 5 intervention groups, each starting with a VitaBit-only phase before receiving the intervention, in order to determine the effectiveness of UPcomplish (**Chapter 6**) as well as underlying mechanisms of effectiveness (**Chapter 7**). Although in our first effect evaluation, we did not find support for effects of UPcomplish in reducing sedentary behavior, we assume that, if further refined and combined, the UPcomplish intervention has some potential.

Main Findings

In a laboratory setting, the VitaBit device showed good accuracy values when compared with direct observation on a minute-by-minute basis (**Chapter 2**). However, this cannot be generalized to free living behaviors, especially, when more specific behaviors, such as riding the bicycle or the car, are involved. Yet, we decided that, since behaviors in daily office life majorly encompass “normal” sitting, standing and walking, that the VitaBit would be suitable to continue with the development of a VitaBit-based intervention. In a pre-test during the intervention development (**Chapter 3**), we discovered that too much background information is not necessary and not perceived as necessary by participants, but that a personal kick-off meeting, personal feedback messages as well as self-monitoring were perceived as helpful. In a pilot test, UPcomplish showed promising results because no participant dropped out and the intervention messages were highly accepted and well understood (**Chapter 3**). The feedback messages were programmed to result in tailored feedback which is implementable on a large scale. However, our effect evaluation found no support for the effectiveness of the intervention neither between- nor within-subjects (**Chapter 6**). When further investigating the reasons for the non-effectiveness of UPcomplish (**Chapter 7**), we discovered that the participants were already highly motivated (i.e. high reported values in psychosocial determinants at baseline) at the beginning of the intervention, which mainly targeted motivation (i.e. determinants). Moreover, among participants who scored a bit lower in baseline determinants, we found that improvements in perceived behavioral control was related to improvements in sedentary behavior, which was not found when correlating the improvements among all participants. The SPORT algorithm (**Chapters 5**), which we developed to incorporate sequential physical behavior patterns, was better able to predict health as compared with a compositional data approach, also incorporating all physical behaviors, but not their sequential daily patterns.

Considerations along the six Intervention Mapping steps

During the six steps of intervention development and during the evaluation, we discovered and coped with a few challenges. The insights that we gained from overcoming these challenges can be used in future interventions targeting workplace health, sedentary behavior or both.

Sedentary behavior and its impact on health and quality of life

Nearly every introduction in manuscripts about sedentary behavior starts with its detrimental consequences: Diabetes Type II, coronary heart disease, obesity (Bankoski et al., 2011; Ekelund et al., 2016; Hamilton et al., 2008). These are consequences that merely occur on the long run, and, except for back pain, the short-term consequences of sedentary behavior, such as perceived vitality or productivity, are either not very well-researched or evidence is mixed (Alzahrani et al., 2019; S.-M. Chen et al., 2009; Faulkner & Biddle, 2013; Hendriksen et al., 2016). According to the Temporal Self-Regulation Theory for Physical Activity, people are more likely to be active if they perceive the benefits of physical activity to be greater and to receive them sooner, while the perceived costs are smaller and later (Hall & Fong, 2015). While in exercise the perceived benefits, such as physical fitness and weight loss, are relatively salient and soon, the beneficial consequences from interrupting prolonged sitting are either not that salient, such as potentially better productivity, or not that soon, such as a decrease in fat mass percentage. This was also found in our effect evaluation (**Chapter 6**), were we did not find support for associations between improvements in sedentary behavior and improvements in self-reported productivity, vitality, perceived stress, perceived pain, or emotional well-being. This not only results in difficulties to measure and communicate short-term benefits of reduced sedentary behavior, but it also illustrates the importance of, possibly artificially, creating and communicating short-term and salient consequences to target group members. Hence, education about the (long-term) cardiometabolic health consequences might help to form an intention to be less sedentary, but the real challenge, which is the translation of the intention into behavior, will require either additional motivators, or sedentary behavior interventions might profit from being combined with interventions promoting other health behaviors, such as exercise.

“Sedentary behavior” is actually a very broad term. Despite a definition of sedentary behavior which is widely used (Tremblay, Aubert, et al., 2017), it does not suffice to define sedentary behavior as sitting (or reclining and lying) with low energy-expenditure, when relating sitting to health, but it is essential to also consider the sedentary pattern: sitting should be regularly interrupted with standing or physical activity (Healy et al., 2008). Additionally, physical activity is not healthy per se: according to the "physical activity paradox", physical activity at work might be less beneficial as compared to physical activity during leisure time (Holtermann et al., 2018). Thus, there are several "rules and regulations" that apply to define healthy physical behavior. The more rules (i.e. predictors) we include, the more accurately we can probably predict health. However, the more rules we include, the more complex the prediction model will become. It will then be unlikely that the insights will be applied in public health and that they will be further investigated and refined in research. Proper knowledge translation with the help of, for example, workshops or open accessible templates (Rychetnik et al., 2012) and open science (Peters, Abraham, & Crutzen, 2012) are therefore essential to ease understandability and enable further application of evidence.

Performance objectives, determinants, and change objectives

When promoting healthy behaviors, it is crucial to break them down into sub-behaviors, i.e. performance objectives, such as "decide to be less sedentary" or "monitor sedentary behavior", because each performance objective is influenced by different underlying beliefs and, therefore, requires different behavior change actions (Bartholomew Eldredge et al., 2016). The UPcomplish intervention aims to promote regular breaks from prolonged sitting and at least 4 hours of standing and physical activity. The underlying performance objectives were based on a process of self-management which includes, among others, self-monitoring, goal setting, discovering barriers, and overcoming those barriers (Clark, 2003). In our effect evaluation, we did not measure all performance objectives. We could observe how often participants registered their sedentary behavior, and we used a proxy for getting an impression on how often participants monitored their behavior. Additionally, from the number of responses to the coach's suggestions, we inferred the participants' engagement in the intervention. Nevertheless, in order to investigate the importance of single performance objectives, we could have measured all of them, for instance, by asking in the surveys, whether and how often participants performed the performance objectives. However, considering the length of the surveys (about 20 minutes), it would have been likely to be perceived as additional burden resulting in fewer compliance. Furthermore, it would have been a challenge to statistically disentangle the importance of unique performance objectives in relation to the behavioral outcomes. On the other hand, we could not support the assumption that reasoned processes might be associated with improvements in sedentary behavior (**Chapter 6 & 7**). It is, therefore, questionable whether standing up requires many sub-behaviors or whether it is merely a single sub-behavior, i.e. "translate the intention into actual behavior" that requires more attention when changing sedentary behavior.

In our effect evaluation (**Chapter 6**) and the analyses of the moderators of effectiveness (**Chapter 7**), we did not find support for associations between improvements of the targeted psychosocial determinants in the UPcomplish intervention (attitude, perceived behavioral control, perceived social norms, intention, and perceived susceptibility) and improvements in sedentary behavior. Only among a sub-group of participants scoring lower in the determinants at baseline, we found that improvement in perceived behavioral control was associated with improvement in sedentary behavior. We assume that it is important to build an intention to be less sedentary in order to decide to participate in a sedentary behavior intervention. Yet, especially the translation of this intention into actual behavior probably requires more than the psychosocial determinants that are targeted in the UPcomplish intervention (Luszczynska et al., 2011). Bridging the intention-behavior gap can be promoted, firstly, by increasing perceived behavioral control (Luszczynska et al., 2011), which, similarly, was found to be the only psychosocial moderator of effectiveness both in our intervention (**Chapter 8**) and in another similar intervention (De Cocker et al., 2017). Yet, if participants are actually limited in their choices to sit less, perceived behavioral control can hardly be promoted solely via persuasive strategies. Additional actions, such as environmental and cultural changes in the companies, need to be put into place (Conroy et al., 2013; Flint et al., 2017; Landais et al., 2020).

Although this will increase the costs of the intervention, it might be essential to yield behavioral change. Secondly, action planning including goal setting and the anticipation of barriers is another strategy to bridge the intention-behavior gap. These methods were used in the UPcomplish intervention and the majority of participants responded to suggestions of goals as well as to the questions about their individual hurdles. However, despite potential increased general awareness helping to remind oneself to interrupt sitting, it might still be difficult to remind oneself to interrupt productive work every 30 minutes also considering other hurdles, such as perceived injunctive social norms (e.g., “Colleagues think, I should work productively and around”) (Mansfield et al., 2018). Thirdly, to help changing habits, it is often suggested to change cues that are associated with these habits (e.g. productive work is associated with sitting) and to change the default options through nudging (Das et al., 2016; Landais et al., 2020). In our Western working society, re-thinking becomes essential: the norm should be standing and walking. Instead of having sitting meetings, new default options, such as walking meetings (mobile technology facilitates taking notes), working together on whiteboards or standing round tables are examples to nudge sitting less in the context of meetings.

Behavior change methods and practical applications

The aim of this dissertation was to develop a sedentary behavior intervention, which helps to reduce sitting via tailored advice, while remaining at low-cost. Therefore, the main application was the VitaBit monitoring toolkit, where participants could daily monitor their own behavior via a mobile phone application and, at the same time, this regularly provided the coach with physical behavior data, which were used to tailor advice. Previously, monitoring behavior was found to be effective (Compernolle et al., 2019; Gardner et al., 2016). However, while monitoring behavior might be very helpful for some participants, others, and potentially especially the ones who could profit from monitoring, might be bothered by regularly thinking of wearing the device. Additionally, causal assumptions need to be critically thought through: it is questionable whether the participants that remember to open the mobile phone application are also the ones who have been contemplating about their behavior already; the participants who drop-out might also be the ones who have not seen improvements in their sedentary behavior.

When translating theoretical methods into practical applications, besides considering the parameters of effectiveness, several trade-offs need to be considered. First, especially in workplace health promotion, employees appreciate low-invasiveness and preciseness of messages, because of timely constraints during working hours (Quirk et al., 2018; Sigblad et al., 2020). However, during this project we learned from informal feedback that especially the feeling of being "observed" by the coach was one of the most helpful strategies. Additionally, after feedback messages 5 to 8, perceived susceptibility ("I think I sit too much and I should reduce my sedentary behavior") dropped, and, at the same time, the number of feedback messages dropped from 2 messages to 1 message per week. Therefore, one might think that continuously coaching participants might be the solution. Yet, at some point, participants need to keep performing the new habits autonomously, which stresses the importance of relapse prevention, building habits, and, possibly gradual instead of abrupt stopping of the coaching. Another trade-off to consider is the balance between a low-cost, automated intervention and a personal, tailored intervention. We learned that participants appreciated the availability of the coach, however, at the same time, most of them assumed that the feedback messages were automated. Although automation helps to safe timely and financial resources, more automation yields less personalization, which is very important in health promotion. Therefore, our idea to compromise between automation and personalization, at least with the current technical status-quo, might have been the optimal compromise.

Intervention Mapping provides intervention planners with a thorough list of behavior change methods. This list is categorized by psychosocial determinants, such as "methods to increase knowledge", "methods to change awareness and risk perception", and "methods to change habitual, automatic, and impulsive behaviors" (Bartholomew Eldredge et al., 2016). However, the authors state that automaticity of a behavior is rather a "characteristic of the behavior" than a standard psychosocial determinant (p. 317). It is suggested to combine specific self-management performance objectives, such as "make a plan, e.g. change a stimulus that elicits or signals a behavior", with determinants, such as awareness, attitude, and self-efficacy, in order to target automaticity of behaviors. The intervention planner therefore needs to consider the theoretical methods that are helpful when changing habitual behavior (e.g. cue altering, nudging, environmental restructuring) when creating performance objectives and the matrices of change objectives. Although Intervention Mapping is an iterative approach, intervention planners are often limited to a tight time frame (e.g. the development of UPcomplish was limited to this dissertation project), and might, therefore, only chronically go through the six Intervention Mapping steps instead of going backwards (especially with a relatively big change, such as changing performance objectives, involving also revisions of the determinants being involved and the matrices of change objectives). Additionally, habits are often considered as "not or barely changeable", and might therefore, also due to time constraints, be neglected during the intervention development. Hence, it might be helpful, to already consider habits, which are considered as very important for behavioral change, in Intervention Mapping step 2. Intervention Mapping might provide the solution for the complexity of including automaticity a bit earlier and stress that, although habits are hardly changeable, they should still be seriously considered. It might be that, when selecting determinant in Intervention Mapping step 2, "importance" of a determinant should be rated higher than its "changeability".

Intervention design and development

When translating our program ideas into the UPcomplish intervention, we profited from closely working together with the VitaBit software team as well as researchers from other disciplines including software developers, economists, biologists, and designers. This enabled a quick translation of program ideas into program components, if resources were available. Despite different ways of working (e.g. research vs. corporate interests) and the challenges being involved, we and the UPcomplish intervention profited from the consideration and the balancing of multiple perspectives.

The VitaBit toolkit was the only tool to our knowledge that offered both a monitoring tool for participants and easy access to raw data. Yet, software projects require complex anticipation of financial and timely resources being involved. For example, unforeseeable factors, such as bugs in the code, new rules and regulations (e.g. General Data Protection Regulation, May 2018), or unexpected changes in the business plan, required prioritization of investments at the cost of, for example, research, development of new widgets, or de-bugging (e.g. automatic synchronization for real-time data). Furthermore, the VitaBit toolkit includes a computer portal where users can monitor more details about their physical behaviors, set short- and long-term goals, and challenge other users. Nevertheless, we learned from feedback that users rarely log-in on their computers and complete both the creation of their accounts and the monitoring of their behavior on their smartphones. Although it is a challenge (in terms of storage space, usability and battery consumption) to include all widgets on a smartphone application, it might be worth considering shifting from a hybrid version (computer portal plus smartphone) to a smartphone-only version. Lastly, for proper posture detection, the small VitaBit sensor needs to be attached somewhere at the thigh, but none of the solutions for attachment are optimal. The currently best solution is to place the device in trouser pockets or, alternatively, attach it to cloths with the help of a magnet. A few participants mentioned that they forgot to take it when changing cloths, that they lost it, or that it was not possible to attach it when wearing skirts during summertime. Alternative solutions that were considered included an elastic strap, like it is used to attach the ActiGraph, a fabric sticker, or a double-sided hydrogel adhesive pad, like it is used for attaching the activPAL. These alternatives, however, were perceived as too uncomfortable for wearing the device for a longer period of time. Therefore, attaching the device with a magnet or placing it in trouser pockets was the best solution that was thought of. This was also reflected in the very low drop-out rates in our effect evaluation due to losses of the device.

Implementation of workplace health promotion programs

One of the biggest challenges that we encountered when implementing and evaluating UPcomplish was the recruitment of participants. Both managers and individuals did often not perceive the need to participate in workplace health promotion, they were not aware of potential advantages or they were afraid of the timely investments being involved. Although we distributed flyers with thorough information about the benefits that participants could expect from UPcomplish and that participation would not require much time, we did not manage to find the number of participants that we needed. Additionally, the participants of the effect evaluation were highly motivated at baseline (high baseline determinants) and perceived themselves to have high quality of life, which is an indication for a selective sample. This observation also generally applies to workplace health promotion, and employees who could profit most are difficult to recruit (Rongen, Robroek, & Burdorf, 2014). Alternatives to distributing flyers, social media and word-of-mouth, are snowball sampling, financial incentives, or random digit dialing, which might be worth considering in workplace health promotion, while respecting ethical necessities.

Sustained implementation of health promotion programs requires intensive planning and often comes with high costs (Fernandez et al., 2019). During the evaluation, we were able to implement the UPcomplish intervention among a big cohort of participants while only one coach was the implementor. However, this was only possible with careful respect for the mental health of the implementor: A business phone, fixed coaching times and free days during the working week helped maintaining a work-life-balance. Moreover, automated feedback messages enabled personalized coaching of about 80 people at once, while only taking about one hour per coaching session. Additionally, both implementation and maintenance of health promotion programs require intensive and, especially, incessant planning and attention, which is only possible, if resources are available. When applying for funding or planning intervention development, also the costs beyond program production and evaluation need to be anticipated. A great and effective program, which is not adopted, maintained and regularly adapted will not have any impact.

Evaluation

Although standard procedures, such as randomized controlled trials, still constitute the golden standard having a control group not receiving the intervention but being measured while another group receives the intervention, this was not possible for our effect evaluation. From experience, without coaching, the majority of VitaBit users stopped using the device after about 2 weeks. This would have provided us with information about their behavior at baseline, but, and this would have been of importance in the evaluation, not during the time that the intervention group would have received UPcomplish. Since we were interested in the effects of all feedback messages of the UPcomplish intervention, two measurements (baseline and post-intervention) was not an option either. Therefore, we applied a stepped-wedge design with several intervention groups starting with time-lags and each group serving as both control condition (i.e. their first week of participation) and intervention condition. Since in a few calendar weeks some individuals already had received the intervention while others were still in their baseline (i.e. control) phase, this enabled between-subjects' comparisons. In order to determine the number of intervention groups, we considered 1) that a higher number of coaching groups would result in higher statistical power and 2) that the more intervention groups received feedback, the longer the period of the coaching would be. Hence, in order to be done latest after 10 months and yet having many data points for between-subjects' comparisons, we decided for 5 intervention groups each starting with time-lags of about 7 weeks. We benefitted from deploying this design. First, since at the time of the effect evaluation, only one coach was available, the stepped-wedge design provided the solution that the coach never needed to coach all participants of the study at ones. Second, since all participants delivered both control and intervention data, this increased statistical power while reducing burden. Third, we were able to perform both within- and between-subjects' comparisons, while not having any control condition. Although comparability between groups and between calendar weeks are questionable (public service vs. information technology company; sitting in summer vs. in winter), centering around means helped to account for these factors in the statistical analyses.

There are multiple reasons why the UPcomplish intervention is offered in combination with the VitaBit monitor. First, in sedentary behavior intervention studies, participants' physical behaviors need to be measured and ideally, with an objective measurement tool. However, wearing the VitaBit device might itself have an effect on physical activity. As behavioral outcome this would be acceptable, but the unique effect of the UPcomplish intervention on sedentary behavior remains unknown. Second, wearing the device without receiving feedback is prone to lower compliance, which ultimately leads to a decreasing potential impact on physical activity. However, our effect evaluation suggested that just wearing the VitaBit monitor without receiving feedback has equal effects on behavior compared to wearing it with feedback. Therefore, the UPcomplish feedback is essential as compliance tool, but again the additional impact of UPcomplish (i.e. decreasing sedentary behavior) is again unknown. This argumentation leads to the situation where it would be interesting to either examine whether a) UPcomplish only versus a no intervention/no VitaBit control group, or b) UPcomplish +VitaBit versus no intervention/no VitaBit control has the desired effects. However, this requires to directly observe participants without them knowing, which ethically would not be possible (McCarney et al., 2007).

Future studies

This dissertation provided new insights into the nature of sedentary behavior at work and how it might be reduced. However, more research is essential to gain insight into what really helps to reduce sedentary behavior at work. As next steps, we suggest the following:

How much and when is sitting habitual. We assume that the concepts from the Reasoned Action Approach (Fishbein & Ajzen, 2011) are specifically important when forming the intention to be less sedentary.

However, as soon as this intention is built, sedentary behavior might be much more determined by automaticity and habits. Therefore, it is important to systematically investigate (separately for all performance objectives) how much variance is explained by habits and how much by intention.

One size doesn't fit all. We assume that it depends on individuals whether they are rather motivated by gamification (e.g. points, leaderboards, challenges) or by information and feedback. In future studies, it needs to be investigated whether there are certain participant characteristics that might further help to refine the UPcomplish intervention to tailor theoretical methods being applied. Additionally, for some people might not be that easy to change to, for example, a standing desk, because they might get physical issues, such as back pain or knee pain. Therefore, it is also important to consider the physical capacity of participants when intervening on sedentary behavior.

Employees who need it most. Since often a selective sample of very motivated employees participates in workplace health programs, it would be interesting to investigate methods that help to recruit employees who score low in baseline determinants. We assume that these employees could profit most from UPcomplish.

How to translate SPORT into recommendations. Applying the SPORT algorithm, we could investigate how long and with which behavior sitting needs to be broken up, and whether sitting bouts can be longer, if someone was more physically active as compared to someone who was more sedentary before the concerning sitting bout. This information could be used to draft sedentary behavior guidelines and real-time interventions.

Hawthorne effect. In a short (e.g. two weeks) study, to prevent drop-out, it could be researched with three groups, one group being directly observed, another group wearing the VitaBit device without having access to the VitaBit application (i.e. without monitoring), and a monitoring group (VitaBit device + smartphone application), whether VitaBit-only is effective in reducing sedentary behavior. This information could help to disentangle VitaBit effects from future baseline measurements.

Combination UPcomplish with other interventions. As mentioned earlier, current sedentary behavior interventions are either very cost-intense or not effective on the long run. However, there is no intervention that offers both a personal coach providing participants with tailored feedback targeting the right psychosocial determinants and environmental changes enabling participants to translate their intention to sit less into actual behavior.

Process evaluation. Our aim was to develop a low-cost intervention. We have data on how long each coaching session took and how many messages were sent that were not from the automated pool of messages. This information could be used to conduct a process evaluation and to gain insights into feasibility and fidelity.

Conclusions

We systematically developed a workplace intervention to reduce and interrupt sedentary behavior. Among employees scoring low in perceived behavioral control and in combination with workplace restructuring, UPcomplish might help to reduce sedentary behavior. It is not only overall sitting time; it is prolonged sitting. It is not only overall sitting time and prolonged sitting; it is the sequential pattern.

Summary

Approximately two decades ago, first evidence emerged about the independent negative effects of sedentary behavior on cardiometabolic and psychological health and well-being. Despite its positive effects on health, moderate-to-vigorous physical activity accounts for only 5 to 10% of the waking day; and it is suggested to not suffice to compensate for the rest of the day which is majorly composed of sedentary behavior. Our society and, especially, the occupational world have become increasingly sedentary. Therefore, occupational health promotion and research have welcomed a new area: Reducing overall sitting time and/or prolonged sitting among office workers. Since then, research on the prevalence, the epidemiology, or the determinants of sedentary behavior has rapidly accumulated. This research supporting the assessment of needs and the formulation of intervention outcomes set the basis for developing interventions. Accordingly, multiple interventions aimed at reducing sedentary behavior among office workers have been developed and evaluated. Notwithstanding some first promising results on short-term reductions of sedentary behavior, available interventions being effective required a personal coach in order to tailor the advice, or a restructuring of the office environment (e.g., height-adjustable desks). Considering the vast costs being involved with these interventions, the purpose of this dissertation was to develop a low-cost, yet tailored, intervention to reduce overall and prolonged sedentary behavior among office workers. Hence, we followed the six iterative steps of the Intervention Mapping protocol which is a framework that guides the systematic development of behavioral change intervention. A first draft of the intervention was developed by merely using evidence from literature and theories. For the refinement of the intervention, missing evidence was gathered within the scope of this PhD project. In general, the intervention consists of two components: a monitoring toolkit, consisting of 1) the VitaBit device, 2) a mobile phone application and 3) a computer portal, and tailored motivational advice delivered by a personal coach, UPcomplish.

The VitaBit device was planned to be one major component of the intervention. It would serve as measurement toolkit for the coach to tailor advice on sedentary behavior patterns and as monitoring tool for the target

group. In **Chapter 2**, we therefore investigated the validity of the device which aims at distinguishing between sitting, standing and activity. Compared with direct observation in the laboratory setting, the VitaBit showed acceptable sensitivity (85.7%) and high specificity (91.2%) for sitting. In the free-living condition, the VitaBit was compared with the Actigraph (GT3X+, ActiGraph, Pensacola, FL, USA) accelerometer (94.4% sensitivity, 95.5% specificity). At this, the VitaBit showed acceptable sensitivity (81.5%) and specificity (84.0%) for sitting. These results confirmed that the VitaBit toolkit would be suitable for using it in a sedentary behavior intervention. Despite its lower accuracy compared to the Actigraph, its advantages entailed that it can be bought at a lower price and that it comes with a ready-to-use coaching portal.

Chapter 3 describes the Intervention Mapping protocol of the systematic development of the UPcomplish and VitaBit intervention including the results of a pre-test of program material and a pilot test of the intervention. Working through the six steps has resulted in a partly automatized, data-driven intervention including 14 feedback messages. The findings of the pre-test suggested to deliver concise messages instead of, for example, videos, and confirmed the importance of a personal introduction between coach and participants. The pilot test showed promising results in terms of program adherence and acceptability. The feedback messages of the final intervention entail five challenges to reduce sitting at work, tailored feedback on the achievement of individual goals and on the sedentary behavior patterns, and motivational support to overcome perceived hurdles to sit less. The chapter ends with a plan on how to evaluate the effectiveness and moderators of effectiveness including the measurements.

In **Chapter 4**, we investigated potential bi-directional and gender-specific associations between sleep duration and physical behaviors (~physical activity and sedentary behavior) among a cohort of Dutch adolescents. The results of the linear mixed effects models indicated that among females, long sleep as compared to optimal sleep duration was associated with more time spent in the following day's health-benefiting MVPA and less time spent in sedentary behavior. Among males, short sleep as compared to optimal sleep was associated with a smaller proportion of the next day being spent sedentary and a bigger proportion being spent in light physical activity. The proportions of physical behaviors were not associated with the sleep duration of the following nights. Considering the weekday specific distribution of physical activity and sleep, the results suggest that the associations between sleep duration and physical behavior might be due to factors such as school schedules. It is suggested to explore these putative moderations in future research by differentiating planned from unplanned physical activity.

For refining the UPcomplish intervention including a guideline on which sedentary behavior pattern is recommended, in **Chapter 5**, we developed and validated an algorithm to represent sequential physical behavior patterns in a single value: SPORT – Sequential, Pattern, Outcome-specific, Real-time, Target group-specific. The SPORT algorithm was compared with a traditional compositional data approach by comparing the explained variance in BMI *z*-scores and fat mass percentages among a cohort of Dutch adolescents. Likelihood ratio tests revealed that the $\text{SPORT}_{\text{linear}}$ models explained significantly (p < .001) more variance compared to the compositional data models. When using a 5-fold cross-validation, the $\text{SPORT}_{\text{linear}}$ models predicted 6% of the variance in BMIz, and 9% of the variance in fat mass, while the compositional data models explained only 2% and 5% of the variance. Hence, guidelines should rather focus on daily sequences of physical behavior patterns than on the composition of physical behaviors. The SPORT algorithm might thus be an adequate approach to calculate single values from complex sequential physical behavior patterns providing a tool to give real-time and day-specific feedback and to formulate target-group and outcome-specific guidelines.

In **Chapter 6**, we examined the short-term effects of UPcomplish. Between May 2019 and January 2020, we applied a stepped-wedge design with 5 intervention groups each starting with time lags of 7 weeks. All participants started with a baseline VitaBit-only week before receiving the 12-week UPcomplish intervention on top of wearing the VitaBit device. Between-and within-subjects, we investigated whether the 14 UPcomplish components have an effect on sedentary behavior and on quality of life (i.e. task and contextual performance, perceived stress, vitality, physical pain, and mental well-being). Despite improving tendencies from the 1st to the 6th feedback message, none of the intervention components showed significant effects in reducing sedentary behavior or improving quality of life when compared to VitaBit-only weeks. We assumed that either the selectivity of the sample due to a selection bias or some characteristics of the intervention have been the reason for this non-effectiveness. An investigation of the moderators of effectiveness was therefore planned.

Consequently, in **Chapter 7**, we investigated whether participant characteristics, baseline psychosocial determinants, baseline physical behavior, or intervention perception were associated with intra-individual improvements in sedentary behavior, determinants, and quality of life. Mostly psychosocial determinants and quality of life at baseline predicted improvements in psychosocial determinants and quality of life. However, improvements in sedentary behavior was not associated with any of the hypothesized moderators. Earlier we had found 1) that the sample scored high in baseline psychosocial determinants (i.e. the sample was selective), and 2) that the intervention was not associated with improvements in psychosocial determinants. Hence, we assumed that the UPcomplish intervention, which focuses on improving determinants, might only be effective for participants scoring lower in determinants at baseline. Post-hoc analyses revealed that among a subgroup of participants scoring lower in the determinants and quality of life factors that seemed to be relevant, only improvements in perceived behavioral control might be associated with improvements in sedentary behavior. An intervention aiming at sitting reductions should therefore focus on increasing perceived behavioral control, which might be even further facilitated if companies are restructured, such as implementing standing meetings or installing height-adjustable desks. Additionally, especially employees scoring lower on psychosocial determinants might profit from UPcomplish.

In **Chapter 8**, we summarized the findings as well as their implication, and we critically contemplated about the methods, results and transferal of this dissertation. We argued that the detrimental consequences of prolonged sitting concern either the long run or are not very well researched, which complicates the application of these consequences as, for examples, motivators. Additionally, we discovered that sedentary behavior is not merely the overall sitting time but more the sequential pattern, which is detrimental. However, uniformly operationalizing this pattern is complex and difficult to communicate to health professionals and target groups. Moreover, we had applied literature to select performance objectives and determinants underlying UPcomplish. These might focus too much on reasoning rather than automaticity. Since we only found support for associations between perceived behavioral control and sedentary behavior improvements, next to promoting perceived behavior control by the help of action plans, it might crucial to also change cues and default options to help translating intentions into behavior. About the VitaBit measurement toolkit, we discussed whether some of the participants rather found it bothering to think of wearing the device instead of profiting from monitoring their behavior. Furthermore, we contemplated about balancing between automation and personalization during the coaching: Personalization of coaching messages can be very cost- and time-intense, but partly automation helps to save resources while keeping the benefits of a personal coach. We further discussed the importance of considering habits earlier in the Intervention Mapping process. We described challenges and benefits that we encountered from working together with an inter-disciplinary team and VitaBit software, as well as the challenges we encountered when implementing and evaluating UPcomplish, such as difficulties of recruiting participants. Consequently, we summarized the benefits and methodological considerations that we encountered during the evaluation study. For example, by applying a stepped-wedge design we were able to increase statistical power while reducing the likelihood of drop-out of participants in a potential waiting control group. Eventually, we discussed potential future research and concluded that UPcomplish might merely be beneficial for employees low in perceived behavioral control and in combination with workplace restructuring and that we always need to consider the complex sequential pattern of sitting rather than the total sitting time of a day.

Zusammenfassung

Vor ungefähr zwanzig Jahren traten die ersten Erkenntnisse bezüglich unabhängiger, negativer Einflüsse von Sitzverhalten auf das Herzkreislaufsystem, die psychologische Gesundheit und Wohlbefinden auf. Trotz positiver Gesundheitseffekte macht Sport nur 5 bis 10% des Tages aus; und es wird angenommen, dass Sport nicht dafür ausreicht, für den Rest des Tages zu kompensieren, welcher hauptsächlich aus Sitzen besteht. In unserer Gesellschaft und vor allem in der Geschäftswelt ist zunehmendes Sitzverhalten zu beobachten, was zur Entstehung einer neuen Richtung sowohl in der Betrieblichen Gesundheitsförderung als auch in der Forschung geführt hat: Reduktion von Sitzzeit und/oder längeren Sitzperioden bei Schreibtischangestellten. Seitdem ist die Anzahl an Forschungsarbeiten über die Prävalenz, die Epidemiologie und die Einflussfaktoren von Sitzverhalten rapide gestiegen. Diese Forschungsarbeit kann sowohl für die Problemdefinition als auch für die Ergebnisformulierung herangezogen werden, um Gesundheitsprogramme zu entwickeln. Dementsprechend wurden bereits einige Interventionen zur Reduzierung übermäßigen Sitzverhaltens bei Schreibtischangestellten entwickelt und evaluiert. Trotz erster vielversprechender Ergebnisse zur kurzfristigen Sitzreduzierung benötigen derzeitige effektive Interventionen entweder einen persönlichen Coach, um Ratschläge und Tipps individuell anzupassen, oder Umstrukturierungen von Büros (z.B. höhenverstellbare Schreibtische). Unter Berücksichtigung dieser enormen Kosten, die diese Programme mit sich bringen, war das Ziel vorliegender Dissertation, eine kostengünstige, aber individuell anpassende Intervention zu entwickeln, um Sitzzeiten, aber auch längere Sitzphasen, von Schreibtischangestellten zu reduzieren. Daher wurden die sechs Schritte des Intervention Mapping Protokolls befolgt, welches ein Leitfaden für die systematische Entwicklung von Gesundheitsprogrammen darstellt. Eine erste Version der Intervention wurde lediglich mit Hilfe von wissenschaftlicher Literatur und Theorien entwickelt. Um diese weiter zu entwickeln, wurden im Rahmen dieser Promotion einige evidenzbasierte Studien durchgeführt. Im Allgemeinen besteht die Intervention aus zwei Komponenten: ein Set zur eigenen Verhaltensbeobachtung, bestehend aus 1) dem VitaBit Sensor, 2) einer

Smartphone App und 3) einem Computerportal, sowie individuell angepasste, motivationale Ratschläge durch einen persönlichen Coach, UPcomplish.

Als eine Hauptkomponente der Intervention war der VitaBit Sensor vorgesehen. Er sollte als Gerät zur Erfassung des Sitzverhaltens dienen, damit der Coach seine Ratschläge zum Sitzmuster anpassen konnte und Mitglieder der Zielgruppe ihr eigenes Sitzverhalten beobachten konnten. Daher wurde in **Kapitel 2** die Validität (Messgenauigkeit) des Sensors untersucht, welcher Sitzen, Stehen und Aktivität unterscheidet. Im Vergleich zu direkter Beobachtung im Laborkontext zeigte der VitaBit Sensor akzeptable Sensitivität (85.7%) und hohe Spezifizität (91.2%) für Sitzen. Im Alltag wurden die Ergebnisse des VitaBit mit denen des ActiGraph (GT3X+, ActiGraph, Pensacola, FL, USA, 94.4% Sensitivität, 95.5% Spezifizität) Beschleunigungssensors verglichen. Hierbei zeigte der VitaBit Sensor akzeptable Sensitivität (81.5%) und Spezifizität (84.0%) für Sitzen. Diese Ergebnisse bestätigten, dass VitaBit für eine Sitzintervention geeignet sei. Trotz dessen niedrigerer Messgenauigkeit im Vergleich zum ActiGraph Sensor beinhalteten die Vorteile des VitaBit, dass er kostengünstiger erworben werden konnte und dass er ein gebrauchsfertiges Coaching-Portal beinhaltete.

Kapitel 3 beschreibt das Intervention Mapping Protokoll der systematischen Entwicklung der UPcomplish und VitaBit Intervention inklusive der Ergebnisse eines Prä-Tests des Programmmaterials und einer Pilot-Studie der Intervention. Die Durcharbeitung der sechs Schritte führten zu einer halb automatisierten, datengestützten Intervention mit 14 Feedback Nachrichten. Die Ergebnisse des Prä-Tests deuteten darauf hin, dass knappe Nachrichten, statt beispielsweise Videos, besser angenommen werden und bestätigten die Wichtigkeit eines persönlichen Kennenlerntreffens zwischen Coach und Teilnehmern. Die Pilot-Studie wies vielversprechende Ergebnisse bezüglich Programmteilnahme und Akzeptanz auf. Die Feedback Nachrichten der finalen Intervention beinhalteten fünf Herausforderungen, um Sitzen am Arbeitsplatz zu reduzieren, und angepasstes Feedback über individuelle Zielerreichung und Sitzmuster. Zudem enthielten sie motivationale Unterstützung, um wahrgenommene Hürden bei der Sitzreduzierung zu überwinden. Das Kapitel endet mit einem Plan zur Effektevaluierung, sowie zur Erforschung von Moderatoren der Effektivität, inklusive Messinstrumente.

In **Kapitel 4** wurden anhand einer Stichprobe von niederländischen Jugendlichen potentielle bi-direktionale und geschlechtsspezifische Zusammenhänge zwischen Schlafdauer und Sitz- und Bewegungsverhalten untersucht. Die Ergebnisse der linearen Modelle mit gemischten Effekten wiesen darauf hin, dass bei Mädchen lange Schlafdauer im Vergleich zu optimaler Schlafdauer mit mehr moderater und energischer Aktivität und weniger Sitzen am nächsten Tag zusammenhängt. Im Vergleich zu optimaler Schlafdauer, hing bei Jungen kurze Schlafdauer mit geringerem Anteil an Sitzen und größerem Anteil an leichter Aktivität am nächsten Tag zusammen. Körperliche Aktivität hing nicht mit Schlafdauer in darauffolgenden Nächten zusammen. Unter Berücksichtigung wochentagsspezifischer Verteilungen von körperlicher Aktivität und Schlaf weisen die Ergebnisse darauf hin, dass Faktoren, wie beispielsweise Stundenpläne in Schulen, Zusammenhänge zwischen Schlaf und körperlicher Aktivität erklären könnten. Es wurde empfohlen, diese potentiellen Moderatoren zukünftig zu untersuchen, indem geplante und ungeplante körperliche Aktivität differenziert betrachtet werden.

Um die UPcomplish Intervention inklusive einer Richtlinie darüber, welches Sitzmuster empfohlen wird, weiter zu verfeinern, wurde in **Kapitel 5** ein Algorithmus entwickelt und validiert, welcher sequenzielle Aktivitätsmuster in einem Wert repräsentiert: SPORT – Sequentiell, Muster (engl.: pattern), Effektspezifisch (engl.: outcome-specific), Echtzeit (engl.: real-time), Zielgruppenspezifisch (engl. : target group-specific). Der SPORT Algorithmus wurde mit einem traditionelleren Ansatz zur Darstellung von kompositorischen Daten (CoDA) verglichen, indem die erklärte Varianz von BMI Z-Werten und von Körperfettanteil in einer Stichprobe von niederländischen Jugendlichen verglichen wurden. Plausibilitätsquotiententests ergaben, dass die $SPORT_{linear}$ Modelle signifikant (p < .001) mehr Varianz erklärten als die CoDA Modelle. Die 5-fache Kreuzvalidierung ergab, dass die $SPORT_{linear}$ Modelle 6% der Varianz in BMIz und 9% der Varianz im Körperfettanteil erklärten, während die CoDA Modelle

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nur 2% und 5% der Varianz erklärten. Daher sollten Empfehlungen tägliche sequenzielle Muster von körperlicher Aktivität, statt nur die Proportionen, berücksichtigen. Der SPORT Algorithmus könnte daher eine angemessene Herangehensweise sein, um einzelne Werte aus komplexen sequenziellen Aktivitätsmustern zu berechnen, was Echtzeit- und tagesspezifisches Feedback sowie zielgruppen- und effektspezifische Empfehlungen ermöglicht.

In **Kapitel 6** wurden kurzzeitige Effekte von UPcomplish untersucht. Zwischen Mai 2019 und Januar 2020 wurde ein Stepped-Wedge Design mit 5 Interventionsgruppen angewandt, welche in Zeitabständen von 7 Wochen starteten. Alle Teilnehmer begannen mit einer Basis-, VitaBit-Woche bevor sie zusätzlich zur Benutzung des VitaBit Sensors die 12-wöchentliche UPcomplish Intervention erhielten. Sowohl intra- als auch inter-individuell wurde untersucht, ob die 14 Feedback Nachrichten einen Effekt auf Sitzverhalten und Lebensqualität (Leistung, Stress, Vitalität, körperlicher Schmerz, und mentales Wohlbefinden) hatten. Trotz leichter Verbesserungstendenzen zwischen der ersten und der sechsten Feedback Nachricht, zeigte keine der Interventionskomponenten im Vergleich zu Basis-VitaBit-Wochen einen signifikanten Effekt auf Sitzverhalten und Lebensqualität. Es wurde vermutet, dass die Gründe dieser Non-Effektivität entweder in der Selektivität der Stichprobe oder in bestimmten Eigenschaften der Intervention wurzelten. Daher wurde eine Untersuchung potentieller Effektmoderatoren geplant.

Infolgedessen wurde in **Kapitel 7** untersucht, ob bestimmte Teilnehmereigenschaften, psychosoziale Faktoren (z.B. Einstellungen, Norm-Wahrnehmungen) und körperliche Aktivität zum Zeitpunkt der Basismessung oder Wahrnehmung der Intervention von Seiten der Teilnehmer mit intraindividuellen Verbesserungen des Sitzverhaltens, psychosozialer Faktoren oder der Lebensqualität in Zusammenhang standen. Hauptsächlich psychosoziale Einflussfaktoren und Lebensqualität zum Zeitpunkt der Basismessung sagten Verbesserungen in psychosozialen Einflussfaktoren und Lebensqualität selbst vorher. Allerdings waren Verbesserungen des Sitzverhaltens nicht mit irgendeinem der vermuteten Moderatoren assoziiert.

Zuvor war herausgefunden worden, 1), dass die Stichprobe bei der Basismessung hohe Werte in psychosozialen Einflussfaktoren aufwies (die Stichprobe war selektiv) und 2), dass die Intervention keine Verbesserung von psychosozialen Faktoren vorhersagte. Daher wurde angenommen, dass die UPcomplish Intervention, welche die Verbesserung von psychosozialen Einflussfaktoren fokussiert, nur für Teilnehmer effektiv sein könne, die vor der Intervention geringere Werte in den vermeintlich moderierenden psychosozialen Faktoren aufwiesen. Post-hoc Analysen mit einer Untergruppe von Teilnehmern, welche bei der Basismessung etwas niedrigere Werte in den psychosozialen Einflussfaktoren und Lebensqualität aufwiesen, die relevant zu sein schienen, ergaben, dass lediglich Verbesserung von Selbstwirksamkeit mit Verbesserung von Sitzverhalten in Verbindung stand. Eine Intervention, die auf die Reduktion von Sitzverhalten abzielt, sollte daher darauf fokussieren, Selbstwirksamkeit zu erhöhen, was weiterhin unterstützt werden könnte, wenn Firmen umstrukturiert werden, zum Beispiel indem Stehmeetings abgehalten werden oder höhenverstellbare Schreibtische installiert werden. Außerdem erschien es wahrscheinlich, dass Angestellte, welche niedrigere Basiswerte von psychosozialen Einflussfaktoren aufweisen, von der UPcomplish Intervention profitieren.

In **Kapitel 8** wurden die Ergebnisse und deren Bedeutung zusammengefasst und Methoden, Ergebnisse und Übertragbarkeit dieser Dissertation kritisch betrachtet. Es wurde argumentiert, dass sich die schädlichen Konsequenzen von vielen, langen Sitzperioden entweder auf die lange Frist beziehen oder noch nicht gut erforscht sind, was beispielsweise die Anwendung dieser Konsequenzen als Motivatoren erschwert. Außerdem wurde herausgefunden, dass die Schädlichkeit von Sitzverhalten nicht nur die gesamten Sitzzeiten sondern auch deren sequenzielle Muster betrifft. Allerdings ist es kompliziert, dieses Muster einheitlich zu operationalisieren und schwierig, dieses dann Fachkräften oder Zielgruppenmitgliedern zu kommunizieren. Des Weiteren war Literatur herangezogen worden, um Verhaltensziele und psychosoziale Einflussfaktoren, welche die Basis von UPcomplish darstellten, auszuwählen. Diese könnten zu sehr auf Rationalität als auf Automatismen abzielen. Da nur Belege für Zusammenhänge zwischen

Selbstwirksamkeit und Sitzverbesserungen gefunden wurden, könnte es essenziell sein, neben der Förderung von Selbstwirksamkeit mit Hilfe von Handlungsplänen auch Hinweisreize und Standardoptionen zu verändern, um die Übersetzung von Intentionen in Verhalten zu erleichtern. Bezüglich des VitaBit Sets zur Verhaltensbeobachtung wurde weiter diskutiert, ob einige der Teilnehmer es möglicherweise eher als störend wahrnahmen, täglich an das Tragen des Sensors zu denken, anstatt von der Verhaltensbeobachtung zu profitieren. Außerdem wurde das Ausbalancieren zwischen Automatisierung und Personalisierung des Coachings betrachtet: Personalisierung von Coaching Nachrichten kann sehr kosten- und zeitintensiv sein, aber teilweise Automatisierung kann dabei helfen, Ressourcen einzusparen, während die Vorzüge des persönlichen Coaches beibehalten werden. Weiterhin wurde die Wichtigkeit diskutiert, Gewohnheiten schon früh während des Intervention Mapping Prozesses zu berücksichtigen. Zudem wurden Herausforderungen und Vorteile, welche durch die Zusammenarbeit mit einem interdisziplinären Team und VitaBit Software entstanden, sowie Herausforderungen, wie Schwierigkeiten, Studienteilnehmer zu rekrutieren, welche bei der Implementierung und Evaluierung von UPcomplish entstanden, beschrieben. Anschließend wurden Vorzüge und methodologische Überlegungen bezüglich der Effektevaluierung zusammengefasst. Zum Beispiel, indem ein Stepped-Wedge Design angewandt wurde, wurde die statistische Power erhöht, während gleichzeitig die Wahrscheinlichkeit von hohen Abbruchquoten bei Teilnehmern einer potentiellen Warte-Kontroll-Gruppe reduziert wurden. Schließlich wurde potentielle zukünftige Forschung diskutiert und damit abgeschlossen, dass UPcomplish nur für Angestellte mit niedriger Selbstwirksamkeit und in Kombination mit Arbeitsplatzumstrukturierung von Nutzen sein könnte und dass man stets komplexe, sequenzielle Sitzmuster statt lediglich die gesamte tägliche Sitzzeit berücksichtigen sollte.

Impact addendum

"The ultimate impact of a health innovation depends not only on its effectiveness but also on its reach in the population and the extent to which it is implemented with high levels of completeness and fidelity."

(Fernandez et al., 2019)

With the UPcomplish intervention (and related studies as described in this dissertation), we aimed to design, produce, and evaluate an intervention to reduce excessive sedentary behavior - with the ultimate goal to beneficially impact office workers' behavior, health, and, ultimately, their quality of life (Bartholomew et al., 2016). The short answer on the question *"what was the societal impact of this intervention?"* is simple: we only found limited impact *so far* - we did not find sedentary behavior reductions, and even though completeness and fidelity during the intervention period were acceptable and high (100%), respectively, the intervention was (also due to the ineffectiveness) not implemented on a larger scale and might not have reached a population being representative of the target population.

This was not the desired outcome - the UPcomplish intervention was "unsuccessful", and did not manage to reach the impact as defined by Fernandez et al. (2019). However, the intervention did not backfire (i.e. no negative effects) and some impact for specific individuals was found. On another level, participating companies have potentially benefitted from their gained reputation as socially responsible considering the health of their employees as important. This reputation cannot only improve their position on to the market but might also influence their staff members, for instance, concerning job satisfaction and motivation to work.

The studies performed during this project aid several conclusions, lessons learned, and suggestions to increase the potential impact. In sum, we learned that:

1) Sedentary behavior is important, yet not easily changeable.
2) Investments need to be made in terms of the recruitment of amotivated participants.
3) An effective intervention requires the implementation of structural changes.
4) Sedentary behavior needs to be operationalized in a way that it better predicts health.

Sedentary behavior is important, yet not easily changeable.

Diabetes type 2, cardiovascular disease (Biswas et al., 2015; Van Uffelen et al., 2010; Wilmot et al., 2012), and mental health problems (Hamer & Stamatakis, 2014; Voss et al., 2014) are examples of the consequences of sedentary behavior. Therefore, we systematically developed our intervention using Intervention Mapping (see **Chapter 3**). This systematic approach included theory and scientific evidence to optimize potential impact, but it was neither effective in improving sedentary behavior nor quality of life. Our study showed that changing sedentary behavior is not easy: none of the determinants predicting reasoned actions were correlated with changes in sedentary behavior and other psychosocial determinants or underlying beliefs need to be investigated.

Investments need to be made in terms of the recruitment of a-motivated participants.

Another explanation of why we believe our intervention was not successful is rooted in the selectivity of the sample (i.e. highly motivated sample) and in lacking environmental structures facilitating sitting reductions during work and daily life. Post-hoc analyses with a sub-group of participants lower in psychosocial determinants (e.g. perceived behavioral control or attitude) revealed that improvements in perceived behavioral control was associated with improvements in sedentary behavior. For those people, this could increase short-term well-being, such as perceived vitality and work performance, and reduce the risk for cardiovascular diseases on the long-term. To increase impact, future studies need to find ways to ensure that the intervention is delivered to those who might actually benefit from our intervention.

An effective intervention requires the implementation of structural changes.

Structural changes need to be created to facilitate long-term effectiveness of sedentary behavior interventions. We found that it is realistic to use cheap accelerometers, such as the VitaBit toolkit, that allow for large-scale measurements and tailored coaching despite lower, yet acceptable, validity values. Moreover, personal coaches, in contrast to automated coaching, are still perceived as important. Although personal coaching comes with higher costs, it was possible to create personal and tailored coaching messages helping the coaches to save a substantial amount of time. For instance, without automated messages, we were able to coach a maximum of 15 persons, while with automated messages, hundreds of people could be coached.

Sedentary behavior needs to be operationalized in a way that it better predicts health.

Another way to increase the impact of the tailored coaching as described above is if the health outcome that individual feedback is based on, better aligns with an individual's *actual* health. We found that an algorithm, which incorporates daily sequential physical behavior patterns in one single value was better able to predict health indicators (e.g. body composition) compared to a compositional data approach. The SPORT algorithm (as described in **Chapter 5**) that incorporates sequential physical behavior patterns can be used to generate individual- and daily-specific sedentary behavior recommendations and, if real-time data are available, to give real-time feedback on physical behavior patterns. Additionally, it is a more accurate predictor for health as compared to traditional approaches that can be applied both in science and in the health sector. Future studies to increase impact should focus on the development and provision of easy calculation tools.

A last structural change that would increase impact is when digital health research and tools are openly shared. Therefore, all data of this dissertation (cleaned and anonymized format), which is the data from the Focus on Strength study (**Chapters 4 & 5**), from the VitaBit validation (**Chapter 2**), from the pre-, and the pilot-study (**Chapter 3**), as well as the data from the effect evaluation and the moderators of effectiveness (**Chapter 6 & 7**) are fully disclosed. We further published or submitted all our manuscripts in open access journal to guarantee transparency and replicability of all our findings. Moreover, the R-script for the tailored coaching messages could easily be adapted to be used for all health behaviors that are measurable and coachable. If we find out, which health behaviors are most relevant for each individual, and they are willing to register the concerning behavior, we could easily increase their health status. This would be the optimal compromise between personal and low-cost, automated coaching, according to the current technical status quo (Summer, 2020).

Conclusion

We systematically developed a workplace intervention to reduce and interrupt sedentary behavior. Although we did not find an overall effect of our intervention, our intervention had some impact for the image of companies, and for the behavior and health of some individuals. With our studies, we highlighted the importance of the field (i.e. sedentary behavior), we cleared the path and suggested focus for future studies, and we started implementing essential structural changes to aid future impact.

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Curriculum vitae

Nathalie M. Berninger was born on the 9th of March in 1992 in Aschaffenburg, Germany. She followed a four-years Bachelor's in Psychology at the Philipps-Universität in Marburg, Germany, which she completed in 2015. Her interest in Health Psychology started early during her Bachelors: She followed an internship at the German Sports University in Cologne and wrote her Bachelor thesis about the 5-week development of motivation among sport initiates. This interest lead to the initiation of her Masters' in Health and Social Psychology at Maastricht University, which she finalized in 2016. She wrote her master thesis in collaboration with VitaBit software and under the supervision of Prof. Dr. Gerjo Kok. This encouraged the continuation of the project within the scope of this PhD project in collaboration with VitaBit and under the supervision of Prof. Dr. Robert Ruiter, Dr. Guy Plasqui, and Dr. Gill ten Hoor. In 2017, she obtained the FPN PhD Matching Fund, which helped to fund her PhD.