Using the Intervention Mapping and Behavioral Intervention Technology Frameworks: Development of a mHealth intervention for physical activity and sedentary behavior change

Abstract

Few interventions to promote physical activity (PA) adapt dynamically to changes in individuals' behavior. Interventions targeting determinants of behavior are linked with increased effectiveness and should reflect changes in behavior over time. This paper describes the application of two frameworks to assist the development of an adaptive evidence-based smartphone-delivered intervention aimed at influencing PA and sedentary behaviors (SB). Intervention Mapping was used to identify the determinants influencing uptake of PA and optimal behavior change techniques (BCTs). Behavioral Intervention Technology was used to translate and operationalise the BCTs and its modes of delivery. The intervention was based on the Integrated Behavior Change Model, focussed on nine determinants, consisted of 33 BCTs, and included three main components: 1) automated capture of daily PA and SB via an existing smartphone application, 2) classification of the individual into an activity profile according to their PA and SB, 3) behavior change content delivery in a dynamic fashion via a proof-of concept application. This paper illustrates how two complementary frameworks can be used to guide the development of a mobile health behavior change program. This approach can guide the development of future mHealth programs.

Keywords: Intervention design; Intervention mapping; Behavioral intervention technology; Physical activity; Sedentary behavior; Integrated behavior change model

Introduction

Increasing population levels of physical activity (PA) can be achieved through multiple levels of interventions (e.g., policy, community), but ultimately requires individual-level behavior change. One approach that offers scalable solutions for the delivery of interventions to aid individual-level behavior change is the smartphone. Ownership of smartphones increased from 35% in 2011 to 64% in 2014 among adults in the United States (U.S.) (Pew Research Center, 2015). Further, U.S. adults spend an average of 34 hours per month using mobile applications (apps) and mobile web browsers, compared to 27 hours a month online with computers (The Nielsen Company, 2014).

Given their inbuilt sensors (e.g., accelerometers, GPS), smartphones provide the ability to collect objective and ecologically valid data of individuals' real world behavior (Kaplan & Stone, 2013). These sensing capabilities can be leveraged to passively capture an individual's movement behavior. Despite differences in device accuracy, existing evidence suggests comparable estimates of PA as measured by Android smartphones or research-grade accelerometers in free-living conditions (Hekler et al., 2015), and that smartphone apps can accurately measure step counts (Case, Burwick, Volpp, & Patel, 2015). Moreover, using smartphone apps, interventions can be delivered using the same device.

Information-technology-based interventions to promote PA are now widely available and have been shown to increase PA with variable success (Broekhuizen, Kroeze, van Poppel, Oenema, & Brug, 2012; Norman et al., 2007). However, they are not widely used, use is discontinued by individuals over time and their positive effects last for limited periods. Typically, the number of logins to IT-delivered interventions rapidly declines after enrolment for most participants (Laing et al., 2014) and throughout the intervention (Duncan et al., 2014). Most current IT-based interventions rely on automated delivery of pre-defined/scheduled a priori content, which is static and does not adapt dynamically as the individual changes behavior. Often, interventions tailor to initial differences between individuals and primarily capture data via infrequent surveys or assessments (e.g. face-to-face). Yet, behavior varies not only between individuals but also within an individual over time (Riley et al., 2011). Requiring engagement from the participant to either self-report PA or wear an additional device like an accelerometer increases the burden on the individual.

While survey data shows that fitness and nutrition apps are the most common health apps used, among smartphone health apps users, approximately half stop using such apps and indicate high data entry burden and loss of interest as the main reasons for doing so (Krebs & Duncan, 2015). For instance, engagement with the MyFitnessPal app (a highly rated and downloaded app on app stores (Gray, 2015)) during a weight loss trial with primary care patients decreased over time, despite participants reporting satisfaction with the app (79%). Reasons for discontinuing use included it was tedious (84%) to enter data (Laing et al., 2014) and was not perceived as easy to use (24%).

Notably, it has been shown that dynamically tailored interventions have superior efficacy over time compared with those that base their tailoring on single or infrequent assessments (e.g. baseline) (Adams et al., 2013; Krebs, Prochaska, & Rossi, 2010). Smartphones allow an opportunity to capture intensive longitudinal data (i.e. continuous, not episodic) in unobtrusive fashion (i.e. reducing respondent burden). The ability to accurately collect information on exposure and to detect dynamic behavior change indicates ideal opportunity to develop 'just-in-time' intervention, delivering content based on people's behavior, as well as capturing their response to the intervention (Spruijt-Metz, Hekler, et al., 2015; Spruijt-Metz, Wen, et al., 2015).

The literature on designing and describing the process of developing PA promotion interventions is extensive, but few resources exist that integrate both conceptual (i.e. theory, evidence) and technological frameworks to describe the process of developing an mHealth program for promoting PA behavior (Crutzen, 2014; Mohr, Schueller, Montague, Burns, & Rashidi, 2014). This paper describes the steps undertaken to develop a dynamic, adaptive, mHealth pilot-intervention using Intervention Mapping (IM) and the Behavioral Intervention Technology (BIT) frameworks, with the aim of influencing both PA and SB duration in healthy but insufficiently active adults.

Methods

Interventions to change behavior are complex since they involve multiple components. These include the behavior change techniques (BCTs) (i.e. a replicable component of an intervention) and the procedures for delivery (i.e. who delivers, when, duration, and mode). Typically, interventions are insufficiently described and many are developed without following a systematic approach (Kok et al., 2016). A behavior change intervention should specify details of both its active content (i.e. BCTs, “the what”) and its mode of delivery (i.e. “the how”). In the present study, we first used the Intervention Mapping (IM) framework to develop a theory- and evidence-based program by identifying the behavioral determinants and/or facilitators from the literature and selecting intervention methods and BCTs thought to influence such determinants (Bartholomew, Parcel, & Kok, 1998). Secondly, the behavioral intervention technology framework was used to specify the procedures for delivery (e.g. library of behaviour change content, rules, workflow) (Mohr et al., 2014).

Conceptual Framework for Intervention Development: Intervention Mapping – “the what and conceptual how”

While there is no consensus (Prestwich et al., 2014), it is acknowledged that behavior change interventions should be grounded in theory, as they are more likely to be effective when aiming to influence determinants and/or facilitators/barriers of behavior (Baranowski, Anderson, & Carmack, 1998; S. Michie, Johnston, Francis, Hardeman, & Eccles, 2008; Webb, Joseph, Yardley, & Michie, 2010). The intervention mapping framework provides a systematic approach to understand the influences on the target behaviour and to use theory in the selection of components to design interventions.

When choosing an appropriate theory, we considered traditional Social-Cognitive models (SCT) (Bandura, 1986), however, these may not be fit-for-purpose for the development of a more adaptive and interactive mHealth intervention (Riley et al., 2011). Limitations of PA behavior theories and the so-called intention-behavior gap identified in many PA intervention studies (Rhodes & de Bruijn, 2013) have led to the development of models that integrate multiple theories and predictors of behavior in an attempt to explain psychological processes that influence PA behavior. One of such is the Integrated Behavior Change Model (IBCM) (Hagger & Chatzisarantis, 2014), which extends beyond deliberative/explicit intentional (i.e. theory of planned behavior (Ajzen, 1991)) and motivational (i.e. self-determination theory (Ryan & Deci, 2000)) processes by taking into account volitional processes (i.e. action planning (Gollwitzer & Sheeran, 2006)) and the non-conscious/implicit processes of behavior (i.e. impulses (Strack & Deutsch, 2004)).

The IBCM was chosen to guide the selection of theoretical constructs to influence PA. However, intervention designers are encouraged to consider all available evidence and interpret how to adequately integrate it, ensuring ample attention is paid to understanding the causes of behaviour before intervention design (Moore & Evans, 2017). Each construct will have distinct intervention and psychological correlates, and the applied utility of IBCM is not established. Since 1) some of the richness (i.e. in terms of construct comprehensiveness) of theories being consolidated may be lost in translation to integrative models (Teixeira, 2016), and 2) intervention mapping permits integrating theories in a more flexible way than afforded by integrative models, constructs from other theories were also considered, such as SCT's self-regulatory or reflective capability.

Taxonomies have been developed specifying the content of behavior change interventions in terms of BCTs (Abraham & Michie, 2008; Susan Michie et al., 2011), and have been used in meta-regressions, linking BCTs to intervention effectiveness (Dombrowski et al., 2012; S. Michie, Abraham, Whittington, McAteer, & Gupta, 2009). The hierarchical classification is now available and incorporates 93 BCTs (S. Michie et al., 2013). This taxonomy is a comprehensive hierarchically-structured set of BCTs that may be used to design interventions and specify intervention content in detail. Conversely, the intervention mapping framework has its own taxonomy, which describes behaviour change methods that intervention designers can select from according to circumstances. These behaviour change methods are general techniques or processes that have been shown to be able to change one or more determinants of behaviour (e.g. self-efficacy) and presumably affect behaviour (Kok et al., 2016).

Using the Intervention Mapping framework, we selected theoretical methods to target theoretical constructs (e.g. perceived social norm, intention, competence) from the IBCM and mapped the theoretical constructs to specific BCTs in order to define intervention content. In conjunction with consulting the taxonomy of behavior change methods (Kok et al., 2016), we undertook a scoping review of the literature of BCTs and their effects on determinants of behavior (Dombrowski et al., 2012; S. Michie et al., 2009; Olander et al., 2013; Webb et al., 2010; Williams & French, 2011). Caution is warranted as interventions typically include combinations of BCTs (i.e. individual BCTs have not been widely tested, some BCTs are more common to cluster than others). Nevertheless, the outlined BCTs have been identified from previous work and behaviour change methods were selected from the IM taxonomy, which includes methods that have been mapped to specific determinants that they can affect (Kok et al., 2016).

The IM framework comprises six fundamental steps that guide the design, implementation, and evaluation of an intervention (Bartholomew et al., 1998). For the purpose of this study, we focused exclusively on the steps that guide the design of the intervention – steps one to three. The first step – needs assessment of the population – included a scoping review to identify the determinants of behavior and what needs to change. The second step – specification of the goal and change objectives – created a matrice of change objectives by defining the behavioral outcomes and how determinants can be affected. The third step – theory-based methods and practical strategies – linked the objectives to the determinants of behavior and identified the intervention methods and respective practical applications (Bartholomew et al., 1998; Kok et al., 2016). Importantly, IM acknowledges that parameters for a theoretical method's effectiveness need to be met and practical applications will deem the method less effective or ineffective when not. Moreover, previous research highlighted the importance of selecting appropriate theoretical methods according to the characteristics of the target population and goals, and not to assume that methods or BCTs will be uniformly effective across conditions (Olander et al., 2013; Peters, de Bruin, & Crutzen, 2013). Step 4 – production of program components – results in the design and production of the intervention materials. This is where IM was integrated with BIT in order to translate the BCTs onto the "user-facing" app features.

Technological Framework for the mHealth Intervention: Behavioral Intervention Technology – "the technical how"

BITs – behavioral intervention technologies – employ tools such as smartphones to support individuals in behavior change. This framework aims to aid the translation of the intervention components into technological features by bringing together expertise from behavioral science and developers (Mohr et al., 2014). BITs include both clinical and usage aims; clinical aims – the "why" – reflect the desired changes in the determinants of behavior and the behavior itself, while usage aims refer to engaging the user with the BIT during the intervention period. Intervention aims are realised by BCTs – the "conceptual how" – such as self-monitoring, goal setting, or review of goals. Each BCT is operationalised via specific intervention components or BIT elements – the "what" – such as user interfaces, reminders, or push notifications. A workflow (i.e. a set of rules) determines when and under which conditions each element (intervention component) is delivered to individuals over time – the "when" (Mohr et al., 2014).

Importantly, usage aims relate to clinical aims, as the usability of the technology will influence the individual's motivation to engage with the intervention. Therefore, the operationalization of BCTs into BIT elements the individual interacts with should take into account characteristics – the "technical how – that increase the likelihood of relevance to the individual, such as media employed (e.g. text, video), aesthetics, and personalisation (Mohr et al., 2014).

The technological implementation of the framework – BIT-Tech – includes four components: 1) profiler, which defines the individual and transmits data to the intervention planner; 2) intervention planner, which chooses the relevant intervention elements and respective characteristics; 3) intervention repository, which may be a database where all the intervention elements are stored; and 4) user interface, which delivers the intervention elements. The content/elements delivered during the intervention is specified in the workflow and depends on the data captured (Mohr et al., 2014).

Results

Using the IM and BIT frameworks we describe the development process of the mHealth activity profile intervention in a systematic way.

Intervention Mapping step 1 – Needs assessment

A needs assessment was fulfilled via a scoping literature review, which demonstrated that both low levels of PA and high SB increase individuals' risk of cardiovascular disease (Maddison et al., 2016). Specifically, different activity profiles were associated with different degrees of cardiovascular disease risk, with the highest risk observed among those with low levels of PA and high SB. These findings illustrated the need for interventions that target both daily PA and SB together.

Current guidelines prescribe fixed PA goals that may be beyond an individual's existing behavior and capacity (i.e. they may not attempt it or fail and get frustrated, leading to nonresponding). Individuals with low levels of PA and high SB typically meet displeasure on initial attempts to be more active and are unlikely to sustain efforts for benefits to occur (Ekkekakis, Parfitt, & Petruzzello, 2011). Moreover, current PA guidelines do not incorporate light intensity PA (LPA) (e.g. standing/breaking up sitting time) (Hamilton, Healy, Dunstan, Zderic, & Owen, 2008) because limited evidence is available on its benefits (Manini et al., 2015; Smith, Ekelund, & Hamer, 2015; Sparling, Howard, Dunstan, & Owen, 2015). However, individuals may be more receptive to replace SB with standing or LPA (Smith et al., 2015), which are activities typically more easily incorporated into daily life, such as walking (Ogilvie et al., 2007) and cycling (Yang, Sahlqvist, McMinn, Griffin, & Ogilvie, 2010).

Input for the IM process took into account individual and interpersonal determinants and showed that PA behavior is predicted by high levels of self-efficacy, intention, beliefs, motivation (i.e. self-realisation via autonomy, competence, and relatedness), planning, social support and cultural norms (Bauman et al., 2012). The literature also highlighted BCTs that can be used to influence these determinants. Table 1 lists examples of the literature on determinants and successful/effective strategies/BCTs.

Insert Table 1 approximately here

Intervention Mapping step 2 - Specification of goals and change objectives

The program goals were derived from the needs assessment. The overall goal of the intervention is to decrease health risks by promoting a healthier activity profile (reducing SB and/or increasing PA). The intervention aims to 1) promote breaks in SB among those who are active but are also sedentary, and 2) to promote both increases in PA and decreases in SB among those who are insufficiently active and also sedentary.

The integrated behavior change model, which combines constructs from the theory of planned behavior and self-determination theory, was used to specify the performance objectives. Five performance objectives – the behavioral outcomes intended to occur on the target population – were specified. A change objective is a definition of what is needed to change on the determinant of behavior to achieve the performance objective. To specify the change objectives, the behavior determinants of a healthier activity profile that are amenable to change were identified based on the literature (step 1). The performance objectives and the hypothesised changeable determinants were linked in the matrix of change objectives (Table 2) in order to specify the change objectives.

Insert Table 2 approximately here

Intervention Mapping step 3 – Theory informed methods and practical applications

Theoretical methods/BCTs that either likely or previously were shown to be effective at influencing the determinants of behavior were chosen for each of the determinants targeted in the intervention (S. Michie et al., 2005; S. Michie et al., 2008). For example, the theoretical method/BCT "instruction on how to perform the behavior" can be applied to influence the determinants of behavior self-efficacy and knowledge.

Next, the selection of promissing theoretical methods/BCTs and practical applications was informed by reviews of the literature, other e- and mHealth PA interventions (Abraham & Michie, 2008; Adams et al., 2013; Direito, Carraca, Rawstorn, Whittaker, & Maddison, 2017; Duncan et al., 2014; Fjeldsoe, Miller, & Marshall, 2010; King et al., 2013; S. Michie et al., 2009; S. Michie et al., 2008; S. Michie et al., 2013; Morrison, Yardley, Powell, & Michie, 2012), and a content analysis of existing PA apps (Direito et al., 2014). The BCTs were linked to their behavior determinants and respective practical applications. For example, practical applications of 'instruction on how to perform the behavior' could include information on how to incorporate activity into one's daily routine provided via printed materials, via a 'how to section' feature in an app that the user needs to go to, or via a message that pops-up on the user's smartphone and is not dependent of user initiation. Further examples are provided in Table 3.

The translation of theoretical methods/BCTs into practical applications requires that the theoretical conditions are met or else effectiveness will be undermined (Bartholomew et al., 1998). For example, the BCT 'demonstration of the behavior' (i.e. "provide an observable sample of the performance of the behaviour (…) for the person to aspire to or imitate") is posited to increase self-efficacy; however this is unlikely to occur if the conditions that must be satisfied in its practical application are unmet (e.g. when the recipient of such BCT does not identify with the role model, it is unlikely the behaviour will be reinforced). In such instances, practical applications deem the theoretical methods/BCTs as less effective or even counter effective.

Insert Table 3 approximately here

The intervention content aimed to encourage increases in PA duration by promoting daily life activities, such as transport to/from work, household chores/ running errands, and PA at work (e.g. walking to a co-worker's desk instead of calling/emailing). Leisure-time PA, such as walking, cycling, or sports, was also promoted. To address the intention-behavior gap, post-motivational BCTs like action planning and problem solving were included to promote the required behavior changes towards a healthier activity profile.

Behavioral Intervention Technology – translating the conceptual how onto the technical how

The intervention methods and practical applications identified in the previous steps using IM were operationalized in components and materials developed in line with the BIT framework. The intervention had two main goals: 1) clinical aims were to increase PA and/or to reduce SB, while 2) usage aims were to encourage participants to carry their smartphone and engage and sustain engagement with the BIT over time. BCTs were utilised to achieve the desired behaviors. Each BCT was operationalized using different elements (i.e. messages, push notifications, graphs). The sensing and computational power of smartphones to capture real world behavior data, process, and react to it, was harnessed to display content based on algorithms embedded in the platform (i.e. workflow). Table 4 presents examples of translation and operationalization of the BCTs into BIT elements (a comprehensive list can be found on Supplementary material 1)..

Insert Table 4 approximately here

Insert Figure 1 and 2 approximately here

The intervention content was adaptive, tailoring the intervention to each individual based on continuous measurement of PA/SB. A research version of the "Movn Activity Sit Pedometer" smartphone app (Moving Analytics, 2016), named AOL, was used to track movement behaviors. Firstly, data captured by the AOL app was used to classify individuals into one of three activity profiles (i.e. couch potato, potterer, or techno-active (Maddison et al., 2016)). Secondly, the proof-of-concept app (TODAY – TailOred Daily ActivitY) accessed movement data generated by the AOL movement tracking app through an application programming interface (API) to deliver intervention content matched to each activity profile (see Figure 3).

Insert Figure 3 approximately here

The user-facing web application for content delivery was developed using Adobe PhoneGap Framework (Adobe, 2016) and PHP scripting language. The application read information from tables stored in a MySQL database hosted on a secure server: 1) individual information (i.e. profiler), such as MVPA and SB to calculate the activity profile and daily goals of the individual, intervention start date; 2) rules/scheduled tasks (i.e. intervention planner), which chooses the relevant intervention elements based on the conditions met; and 3) a library of intervention content/elements (i.e. intervention repository), such as messages, images and links to be displayed.

On a daily basis, the TODAY app read the activity profile, calculated the day of the intervention for each individual, and selected the appropriate content/elements to be displayed on the user interface if the app was opened. A push notification was sent daily at 10am aiming to promote user engagement with the app (i.e. usage aims).

Discussion

The intervention mapping and behavioral intervention technology frameworks were used in combination to systematically develop a theory based mHealth activity profile intervention. Designing interventions using a systematic approach increases the likelihood of effectiveness and additionally contributes to the growing evidence on how the ingredients of interventions and their practical applications impact effectiveness. This article illustrated a systematic method to develop mHealth interventions combining conceptual and technological frameworks and contributes to future enhancements in the development of mHealth-based behavior change programs.

Designing behaviour change interventions involves a complex set of decisions and ways to tackle intervention development specific for mHealth delivery mediums are scarce. We exemplified a practical application of the steps involved in a systematic method to design such interventions through the characterisation of the behaviours of interest (i.e. main facilitators and barriers of PA/SB), selection of the behavioural constructs (using IBCM as a model of behaviour, and application of specific techniques (i.e. intervention methods and BCTs) to bring about change using mHealth technologies (i.e. intervention planner, elements, workflow). Reporting the rationale and providing a comprehensive description of the intervention in a systematic way provides an example of designing mHealth interventions that others may find helpful. By using the intervention mapping framework we provide a detailed intervention rationale, which will contribute to the interpretation of findings and may facilitate future replication, adaptation, and improvement. The BIT framework supported the communication between developers and behavioral scientists and aided the translation of BCTs into elements, characteristics, and workflow.

Although content delivered was individually tailored to the activity profile of the individual over time (as assessed by the smartphone, not self-reported), the degree to which content was tailored can and should be further specified by taking into account multiple factors. For example, tailoring to individual characteristics such as age, sex, health literacy or theoretical constructs, such as self-efficacy or intention, is likely to result in higher personal relevance and contribute to effectiveness (Head, Noar, Iannarino, & Grant Harrington, 2013; Morrison et al., 2012). Importantly, IM calls attention to the existence of parameters for effectiveness of methods and that their translation into practical applications without paying enough attention to such conditions will impact their established effectiveness. Additionally, the practical application of methods will always likely be more effective when taking into account its congruency with aspects such as fit with the target population, culture, or context (Moore & Evans, 2017).

A number of considerations on the nature of this work are warranted. This is not meant to be a panacea for PA/SB interventions using mHealth technologies, but instead illustrate a scientific approach to the development of mHealth PA behaviour change interventions. Careful interpretation and refinement of the steps here illustrated are warranted in order to make sure that all available evidence is adequately integrated as part of intervention design. A major limitation of the example ilustrated was its explorative nature. For example, we did not focus on a specific population, nor did assess their specific beliefs, intentions, or motivations. We were experimenting the combination of the IM and BIT frameworks to appraise its fitness and usability, particularly in the translation of intervention methods / BCTs onto technological features (i.e. app features). Since interventions and behaviour will always be changed in specific populations and contexts, intervention content (e.g. messages) must be specific to the target population, their beliefs, determinants, and context, so that the translation of intervention methods to practical applications are tailored and consequently more likely to be effective.

Given the explorative nature of our work we selected determinants based on a scoping literature review. A needs assessment step fostering a user-centered approach by conducting interviews or focus groups with the target population is key. Many interventions do not work well because often we fail to identify what needs to change. Therefore, intervention designers should aim to promote a participatory research approach whereby the identification of barriers, facilitators and desires are taken into account in the development process to ensure engagement and usability (Hingle, Nichter, Medeiros, & Grace, 2013).

Alongside a proper needs assessment, (mHealth) intervention designers (and future iterations of this work) should aim to augment the quality of translation of behaviour change methods onto practical applications. The same theoretical method or BCT can be translated into practical applications in numerous ways depending on contextual factors (e.g. population, seting), and attending to the parameters for effectiveness can improve method sociocultural relevance. Digital technologies can be harnessed to ensure congruency between the methods' parameters for effectiveness and both the target population and contextual characteristics in order to reach optimal content delivery (Moore & Evans, 2017). For example, theoretical methods to change an individual's self-efficacy belief to break prolonged sitting at work may include modelling, whereby a video in a work setting could demonstrate employees doing easy/quick exercises using office furniture, or role-models' testimonies with ways around interrupting sitting, such as how they take phone calls standing or have walking meetings. One of the parameters of effectiveness of the theoretical method modelling is that the recipient must identify with the model (e.g. age, gender, ethnicity). Therefore, translating a practical application of the method modelling harnessing digital technologies could involve showing videos of different role models according to the demographic characteristics of the recipient (e.g.video with male role model showed to male recipients only).

While mHealth interventions including effective methods/BCTs may increase their potential effectiveness in changing behaviour, if the operationalization of such methods is not in line with their parameters of effectiveness, they are unlikely to contribute to behaviour change. The quality of operationalization of methods/BCTs (in this exploratory study) requires improvement in order to realise their full potential. For example, for action planning to be effective, the recipient must have a pre-exisiting intention to perform a behaviour. mHealth technologies could capitalize on a profiler (i.e. what defines the individual, e.g. via sensing or self-reported assessment of intention) and workflow (i.e. a set of rules, e.g. “IF intention > x value, THEN operationalize action planning, ELSE…) to determine when action planning would be presented to individuals. A different example could be the importance of the timing of provision of choices while trying to foster autonomous motivation – it should occur when relevant (e.g. when choices are available and where enactment is possible). Likewise, social support BCTs should be operationalized especially when individuals face challenges (e.g. when goals are frequently not met) in order for relatedness needs to be satisfied and potentially contribute to autonomous motivation.

BCTs do not have an ascribed effectiveness and the way they are operationalized and presented to individuals may have as great or larger impact as the BCT itself (S. Michie et al., 2013). Moreover, the optimal combination of BCTs for each context (i.e. what works for whom, in what settings) is unknown, as are interactions with each other (i.e. some BCTs may have synergistic effects and amplify each other, whilst others may undermine each other’s effects). As an example, while intervention content attempted to promote self-reflection and avoid controlling communication to promote autonomy-supportive interactions, operationalization of some BCTs, such as “discrepancy between current behavior and goal”, may be perceived by individuals as judgmental and controlling, and consequently hinder autonomous motivation.

The full capability of mHealth technologies to tailor content as behaviour change occurs is yet to be realised. For example, in this explorative study, among intervention tailoring variables related to PA/SB behaviour were, as observed in Figure 3, mCOV (a measure of movement) and day. The same figure highlights the potential to include many other tailoring variables, such as individual beliefs, motivation, or self-efficacy. mHealth technologies allow for repetitive longitudinal measurement and intervention content to be adapted based on input from other tailoring variables. Computational models based on dynamical systems in order to account for within-individual fluctuations of behaviour (e.g. day, week, season) based on traditional behaviour change theories like SCT are being developed (Riley et al., 2016). To date, research on the underlying mechanisms of the effectiveness of mHealth interventions is scarce and process data has mostly been obtained via self-report. By using the BIT framework to specify decisions on the intervention elements, characteristics, and workflow, will contribute to a growing body of data on how such decisions relate to effectiveness (Mohr et al., 2014).

Conclusions

The Intervention Mapping and Behavior Intervention Technology frameworks were used in a complementary manner to aid the intervention development of a theory-evidence-based mHealth intervention. The IM contributed to the identification of the determinants and optimal theoretical methods to promote behavior change, while the BIT contributed to the translation of the theoretical methods into practical applications and respective technical operationalization.

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(This section was moved to the title page file for review purposes).

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