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Original Article

Digital Health and Computer-Tailoring: Opportunities and Challenges in Moving the Field Forward

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In present times, digital health interventions are pervasive. This is not surprising, as the Internet is accessible 24/7, available independent of a person's location, and the most consulted medium when people need health related information (van de Belt et al., 2013). As described in another article published in the European Health Psychologist (Smit et al., 2019), we define Digital health as *"the use of digital information and communication technologies to improve health and increase the chances of sustainable healthcare for all"*. According to this definition, digital health interventions include but are not limited to eHealth, mHealth, telemedicine as well as wearable devices.

Computer-tailoring is an inherent part of many digital health interventions. This is achieved through the programmed delivery of intervention materials that are tailored – or adjusted – based on an assessment of the characteristics, beliefs and/or behaviour of each individual user (de Vries & Brug, 1999). In contradiction to generic forms of digital health communication (e.g., health information websites), computer-tailored interventions provide participants with personally relevant information. In line with what is described in the Elaboration Likelihood Model (Cacioppo & Petty, 1984), this information is consequently more likely to be read, to be used and engaged with, and to be processed in depth. This results in beneficial outcomes such as greater recall and enhanced initiation or continuation of the communicated health behaviour (change) (Cacioppo & Petty, 1984; Kreuter et al., 1999; Nikoloudakis et al., 2018; Ritterband et al., 2009).

A convincing amount of evidence exists showing that computer-tailored digital health interventions can (cost-)effectively change health behaviour for the better (Cheung, Wijnen, & de Vries, 2017; Lustria et al., 2013; Schulz et al., 2014). While this has led to calls for wide-scale implementation of digital health interventions, the modest effect sizes obtained from studies of efficacy remind us that there is still room for improvement. This also extends to applications targeting intermediaries (e.g., health care professionals, de Ruijter et al., 2018) and intermediate behaviours (e.g., smoking cessation support tool uptake, Gültzow et al., 2021). Furthermore, new technologies such as artificial intelligence bring about new opportunities as well as challenges that need attention if we are to ultimately bring the field forward.

With all this in mind, and to join forces in moving the digital health field forward, a new Special Interest Group (SIG) on the topic of Digital Health and Computer-Tailoring was launched during the 2019 annual conference of the EHPS (Smit et al., 2019). The mission of this SIG is *"to advance digital health and computer-tailoring research and to provide a forum for EHPS members to discuss new evidence, underlying mechanisms and specific components of digital health interventions that may lead to enhanced behavioural outcomes"*. The guest-editing of this special issue in the official EHPS bulletin, i.e., the European Health Psychologist, is one of the steps we have taken since the SIG's launch in 2019, to provide such a forum.

We are very proud of the final collection of articles included in this special issue, covering a wide range of aspects related to digital health and computer-tailoring. To elaborate, Villinger et al. (2021) present the results of a smartphone-based Ecological Momentary Assessment study that aimed to assess health as well as risk behaviours and COVID-19 related risk perception in a real-world setting, capturing daily variations and changes over time in the context of the COVID-19 pandemic, to understand how variations in risk perception relate to behaviours. The main findings of their study were that perceived likelihood of having contracted COVID-19 was significantly higher on days when participants had had more in-person social contacts and left their homes for multiple reasons. Furthermore, there was substantial variation in health-related behaviours, including eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behaviour, and overnight sleep not only between, but also within individuals and on a daily basis.

The latter finding of the study by Villinger et al (2021) relates to the framework presented in the second article of our special collection, authored by Marques and Guastaferro (2021). They argue that MOST – which stands for Multiphase Optimization Strategy – can provide a valuable contribution to the development of behavioral interventions. MOST is an engineering-inspired framework to support the development, optimization and evaluation of multicomponent behavioral interventions. The framework includes three phases: Preparation, Optimization and Evaluation. In particular, the authors argue for the integration of the optimization phase within the standard intervention development process in order to increase the likelihood that resultant interventions are effective, parsimonious, and able to be readily implemented. By putting emphasis on optimization, MOST values the empirical process of identifying an intervention that produces the best expected outcome obtainable given key constraints imposed by the need for affordability, scalability, or efficiency. The MOST framework lends itself to the use of adaptive experimental research designs during the evaluation phase. These include for example, Just-In-Time-Adaptive-Interventions (JITAIs; Nahum-Shani et al., 2015) that are especially designed to consider daily fluctuations in health-related cognitions and behaviors, e.g., as described in the article by Villinger et al. (2021).

This brings us to the third article included in this special issue, in which Wunsch et al. (2021) provide a conceptual overview of JITAI research and discuss the challenges and opportunities with a focus on physical activity interventions. In their position paper, the authors describe key advantages of JITAIs as constituted by the potential to 1) tailor interventions to individual users' needs in real time to deliver support at the most promising moment, 2) adapt to input data, 3) be system-triggered, 4) deliver goal-oriented interventions, and 5) allow for customization depending on the users' preferences. Because of these characteristics, JITAIs may increase engagement with and effectiveness of health behavior interventions. Nevertheless, the authors also argue that most existing JITAI research shows considerable methodological shortcomings, with the most prominent being that JITAIs are not described in a standardized fashion which complicates extracting information on effective components of the interventions to inform future research and practice. The authors conclude their work by stating that although JITAIs are a promising feature in mHealth applications, a sound theoretical basis is still lacking and interdisciplinary expert-panels are needed to refine development, implementation, and evaluation of JITAIs and to keep pace with technological innovations – as described by Marques and Guastaferro (2021), MOST might be a framework that is helpful here.

The last paper in this special issue refers to technological developments as well, detailing how routinely collected data and novel self-assessment methods can be used in computer-tailoring to measure psychological constructs and address the key challenges of low levels of engagement and high attrition that are likely caused by the high perceived user burden when completing the long, theory-based self-report questionnaires needed for the individual assessment that forms the basis for computer-tailored feedback generation. Building upon novel technological possibilities, Short et al. (2021) describe several examples of how routinely collected data can be used as input for computer-tailoring, one being that it may be possible to deduce exercise habits using a smartphone by combining automatically collected data on behavior frequency (e.g., using accelerometers, GPS or movements between cell towers) with data on contextual cues (e.g., location, time of day, interactions with specific people). They also describe several novel ways in with data can be purposively sampled in a less burdensome manner as compared to self-report questionnaires, one example being the adoption of game-based elements such as avatar selection to assess real as well as ideal user self-perceptions. The authors conclude their article by discussing the challenges one may encounter when using the proposed methods for routinely collecting data and/or self-assessment, and providing multiple recommendations for future research and practice, which are hoped to stimulate further momentum in this area.

All in all, we have very much enjoyed putting together this special issue about digital health and computer-tailoring and hope it will provide food for thought and scholarly discussion, so that we, as a community, can ultimately move this exciting field forward by taking advantage of the (technical) opportunities and overcoming the challenges we will encounter.

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Original Article

The Development of Effective and Tailored Digital Behavior Change Interventions: An introduction to the Multiphase Optimization Strategy (MOST)

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Digital behavior change interventions (DBCI) are uniquely equipped to deliver personalized solutions to influence complex and challenging health behaviors. Rich information about individual(s) and their context may be used to deliver the best suited approach to behavior change. However, there is a lack of precision regarding what needs to be personalized or tailored or adapted (e.g., is it the choice of the content of the intervention, its dose or is it the mode of delivery?) and how (e.g. fixed based on baseline values, or adaptive from contextual information). Traditional approaches to DBCI development and testing wherein the intervention is assembled and tested as a package do not provide answers to these questions. Thus, to advance intervention science, dynamic approaches to the development of DBCI are needed. The aim of this paper is to introduce the Multiphase Optimization Strategy (MOST) as a potential solution to this need. In the context of a DBCI, it is possible to develop a fixed intervention wherein all participants receive the same intensity of intervention, but more commonly there is usually a degree of tailoring or personalisation of the content or delivery which necessitates the development of an adaptive intervention, such as a Just-in-Time Adaptive Intervention (JITAI; Nahum-Shani et al., 2018). We will provide a brief overview of the application of MOST to the development of an adaptive DBCI. We offer a suggestion for the way in which MOST may be integrated with other DBCI development frameworks, such as the Behavior Change Wheel (BCW; Michie et al, 2011; Michie et al, 2013), to improve the effectiveness and tailoring of DBCI. As an approach rather than an off-the-shelf method, our intention is to inspire intervention scientists working in the digital behavior change space to creatively integrate innovative and dynamic approaches to intervention development to maximize public health impact.

Overview of MOST

MOST is an engineering-inspired framework to support the development, optimization and evaluation of multicomponent behavioral, biobehavioral, biomedical, or social-structural interventions (see Collins, 2018 for a more comprehensive overview). In contrast to traditional intervention development approaches, MOST introduces a phase of optimization prior to evaluation. Optimization is the process identifying an intervention that produces the best expected outcome obtainable (i.e., effective) given key implementation constraints. A constraint is anything that could impact implementation such as participant time, cost, or provider capacity. Thus, an optimized intervention is one that is not only effective but is also moving toward desired attributes of affordability (i.e., can be delivered without exceeding budgetary constraints), scalability (e.g., can be immediately implemented with fidelity), and efficiency (e.g., comprised only of active components). The goal is to empirically identify which intervention components work and which do not work, which ones work well together, and under which contextual characteristics. Using MOST, an intervention scientist over time is able to balance intervention effectiveness with affordability, scalability, and efficiency.

MOST consists of three phases: Preparation, Optimization and Evaluation (Figure 1). In the preparation phase, scientists will: develop and refine their theoretically and empirically derived conceptual model; identify candidate components; conduct any pilot work (e.g., hypothesis generating, unpowered experiments designed to assess acceptability and feasibility); and, identify the optimization objective. The optimization objective is the goal of the optimization, or stated differently, it describes how you will balance intervention effectiveness against affordability, scalability and efficiency. Reflecting the goal that you want to achieve, the optimization objective considers any constraints on implementation; for example, "the most effective intervention delivered in less than 30 minutes." Accounting for this constraint in the design of the DBCI, the optimized intervention is not only effective, but also efficient and has increased potential for scalability.

In the optimization phase of MOST, the scientist conducts an optimization trial to identify and build the optimized intervention. When matched appropriately with research questions and intervention type (i.e., fixed versus adaptive), the optimization trial provides the empirical data needed to identify which components meet the optimization objective and will be included in the optimized intervention. It is beyond the scope of the current paper to provide details about all possible experimental designs used in the optimization trial (readers are referred to Collins, 2018 for an overview), however the optimization of an adaptive intervention necessitates the use of an adaptive experimental design for the optimization trial. Common adaptive experimental designs used in MOST are the Sequential, Multiple Assignment Randomized Trial (SMART; Almirall et al., 2018), Micro-Randomised Trials (MRT; Klasnja et al., 2016), or System Identification experiments (Heckler et al. 2018). Regardless of the experimental design selected, the goal is to understand the effect of each component on the outcome of interest individually and in combination with other components.

In the evaluation phase, the effectiveness of the optimized intervention is compared to a suitable comparator (e.g., control, placebo, standard of care). Generally, this comparison is done via a randomized controlled trial, but this is not a requirement of the evaluation phase - any experimental design matched to the research question is suitable. Inherent in the MOST framework is the engineering-inspired continual optimization principle, which holds that even an optimized intervention may be further optimized. Optimized DBCI have the potential to hasten the progress of translational research, thereby maximizing the potential public health impact. Box 1 offers a high-level overview of a hypothetical example of how MOST may be applied to the development of a DCBI.

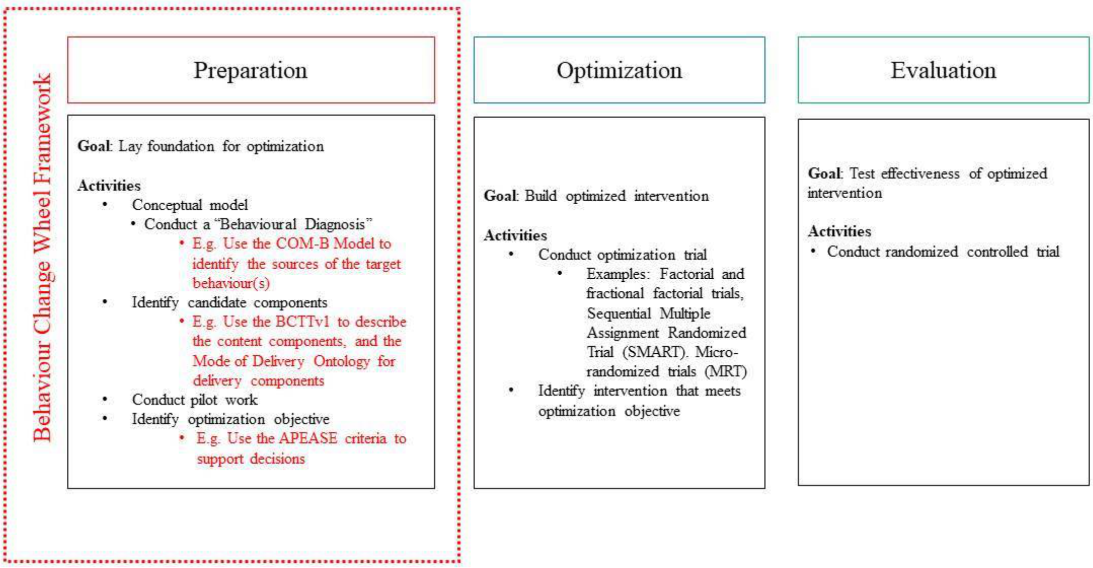
Ensuring that the DBCI meets the needs: bringing frameworks together

Overall, the MOST framework and other intervention development frameworks from behavioral sciences are complementary, especially in the preparation phase. At a minimum, we believe there are two ways in which MOST may be integrated with other frameworks that could contribute to selecting and building DBCI that are effective and tailored to the needs of the target population.

Supporting the conceptual model and selection of components. As described above, hallmark activities of the preparation phase are the development of the conceptual model and the identification of the candidate components. These preparatory tasks ensure that the DCBI identified in the optimization phase and tested in the evaluation phase of MOST will indeed target the individual and/or social factor/determinants that can bring about the desired behavioural changes. Moreover, these preparatory tasks ensure the intervention includes the techniques/strategies or components that can actually impact on these factors. However, the MOST framework makes no assumptions about the process of achieving these activities. Other behavioral science frameworks may support this preparatory work. In this paper we describe how the Behaviour Change Wheel (BCW; Michie et al, 2011; Michie et al, 2014), one of the main frameworks currently used for developing DBCI, may augment this preparatory work. Figure 1 describes how the BCW may be integrated with MOST to achieve the goals of the preparation phase.

The BCW framework provides detailed standardized guidance on how to develop an effective behavioural intervention. The process begins with a "behavioural diagnosis" which consists of three steps: (1) identification of the target behaviours(s) and population; (2) specification of the behaviours - who needs to adopt the behaviour, when and what needs to be done; and (3) identification of the sources/factors influencing the target behaviours. The third step is particularly relevant for the development of a conceptual model in the preparation phase of MOST. The BCW framework proposes the use of the COM-B model (Michie et al, 2011; Michie et al, 2014) to categorize/conceptualize the factors - barriers and facilitators - influencing BEHAVIOURS in relation to the physical and psychology CAPABILITY (e.g. stamina, planning skills), social and physical OPPORTUNITY (e.g. social support) and reflective and automatic MOTIVATION (e.g. habits, beliefs, goals) (For further reading, consult Michie et al, 2011; Michie et al, 2013). Once the behavioural diagnosis is finalized, the next steps in the BCW framework are to identify what the intervention will consist of (intervention functions) and map them to the COM-B model (or formal theory selected). By intervention functions we mean strategies such as modelling, enablement,

Figure 1. Overview of the phases of the multiphase optimization strategy (MOST) with an example integrating the Behaviour Change Wheel Framework (Michie et al, 2011, 2014) in the preparation phase



persuasion, environmental restructuring, or coercion. These interventions functions are then further specified into specific behaviour change techniques that will be implemented (e.g., goal setting, demonstration of behaviour, social comparison, self-monitoring, problem solving (see Michie et al, 2013, 2015 for a full list of behaviour change techniques that are described in the Behaviour Change Techniques Taxonomy v1)) and the way in which the techniques will be delivered (i.e., their mode of delivery (Marques et al, 2021)) and technical specifications. The intervention functions and behavior change techniques may correspond to (or inform) the "candidate components" in the MOST framework.

Ensuring a shared language. MOST can also benefit from linking with other approaches to the standardization of components. Classification systems such as the Behaviour Change Techniques Taxonomy (Michie et al. 2013, 2015), the compendium of self-enactable techniques (Knittle et al., 2020), the Intervention Mapping taxonomy of behavior change methods (Kok et al, 2916) or the Behaviour Change Intervention Ontology (Michie et al., 2020), can bring a standardized approach to MOST by classifying the components of the MOST- based intervention in an unambiguous way using a shared language. Not only this will improve reporting of what goes on in interventions and, consequently, accumulation of scientific knowledge, but mainly using these standardized classification systems can support researchers and interventionists in identifying, selecting and optimizing the candidate components for the intervention. In the context of MOST, by components we mean aspects that can be selected, modified and tested in the context of a behavioural intervention, such as the content of the intervention (e.g., techniques such as goal setting, self-monitoring or stress management), the source of delivery (Norris et al., 2021), its mode of delivery (e.g., using a video, audio, wearable; Marques et al., 2021), the schedule and dose of delivery, and tailoring options (Michie et al., 2021).

Advancing the potential of MOST through international collaborations

Using the MOST framework for developing, optimizing, and evaluating DBCI, it is possible to identify which intervention components work and which do not work, which ones work well together, for whom, and their synergistic effects. This identification is crucial to avoid research waste and build efficient and scalable DBCI, at the same time taking into consideration the level of personalisation and adaptation that is needed to maximise the potential of digital solutions in changing health behaviours and improving health outcomes. MOST has been applied to a number of public health priorities including smoking cessation (Piper et al., 2016), obesity (Spring et al., 2020), heart disease (Celano et al., 2018), HIV (Caldwell et al.,2012; Gwadz et al., 2017), palliative care (Wells et al., 2020), and the prevention of sexually transmitted infections (Wyrick et al., 2020; Tanner et al., 2021). In the U.S., more than 100 projects using MOST have been funded by the National Institutes of Health. In Europe, though MOST is a newer approach slowly gaining attention from the research community, other behavioural science frameworks for intervention development, such as the BCW, are widely disseminated, tested and implemented. There is an opportunity to borrow expertise across both sides of the Atlantic to advance the science of DBCI.

As described, these frameworks can be integrated with MOST to improve the preparation phase and ensure the necessary level of standardization that can effectively contribute to evidence accumulation, but the ways in which these frameworks can be integrated require further discussion and analysis. In addition, we believe the establishment of international U.S. and European research networking and collaborative opportunities would be a major contribution to improve our current knowledge on what and how to select, and implement optimisation designs in the context of DBCI. To pursue this endeavor, the Special Interest Groups, and expert networking opportunities provided by scientific societies such as The European Health Psychology Society, the Society for Behavioural Medicine, or the International Behavioural Trials Network could play a major role. Further, in collaboration with other colleagues we will be soon launching an expert consultation exercise on the applications of the various experimental designs that MOST can include.

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Box 1. A hypothetical example of how to apply MOST to the development of a digital behavioral change intervention

Aim: To develop a mobile-based intervention designed to promote adherence to physical distancing guidelines during the COVID-19 pandemic

Preparation Phase

- *Develop a conceptual model*: The research team conducts a scoping literature review to identify the core barriers related with capability, motivation, and opportunity related to the outcome of interest. From the literature, and based on behavioral change theory, the team identifies the following core aspects to be addressed in the mobile-based intervention:
    1. Beliefs about consequences
    2. Context facilitation (physical and social)
    3. Improving trust in government
- *Candidate components identified*: The core aspects identified in the conceptual model are translated into the behavior change techniques to be used in the intervention component. For example:
    1. Information about how keeping physical distance from others can prevent COVID-19 spread; reinforce values around COVID-19 protective behaviours;
    2. Support in finding ways to be with family, friends or colleagues, keeping the physical distance (e.g. prompts to enact at times where the person is usually in contact with others); Empowering to take action and influence others in the community;
    3. Regularly updated information about physical distance guidelines from credible health authority sources;
- *Pilot test components*: Components are tested in pre-posttest design to determine acceptability and feasibility of each component.
- *Identify optimization objective*: The team decides to prioritize efficiency; thus, the optimization objective is the most effective intervention delivered in less than a total of 15 minutes of participant time.

Optimization Phase

- *Conduct optimization trial*: The team chooses a SMART design to identify which combination of components produces the greatest improvement in adherence to physical distancing guidelines.
- *Identify optimized intervention*: Empirical information from SMART trial indicates that optimized intervention should consist of components 1 and 2.

Evaluation Phase

- *Conduct randomized controlled trial*: Compare the optimized intervention to a control condition consisting only of information about the distance that should be kept.

Original Article

Measuring psychological constructs in computer-tailored interventions: novel possibilities to reduce participant burden and increase engagement

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Abstract

Within the field of health psychology, there has been an enormous increase in behaviour change interventions that use digital technology. Answering questions and providing tailored feedback based on the answers provided by participants is the key working mechanism when using computer-tailoring in behaviour change interventions. This behaviour change method has proven to be (cost-)effective and results in participants being exposed to material that is tailored to their social-cognitive profile. At the same time, answering questions to assess this profile increases participant burden, which might contribute to low levels of engagement and high attrition - two of the key challenges in digital health.

This article provides insight into how routinely collected data and novel self-assessment methods can be used in computer-tailoring to measure psychological constructs and address these key challenges. The examples presented suggest that the development of novel proxy measures for measuring psychological constructs relevant to computer-tailoring is indeed possible. However, the extent to which measures are valid and actually do reduce participant burden and have other potential benefits is speculative and needs further investigation. The recommendations provided for future research and practice are hoped to serve as a stimulance for driving further momentum in this area.

Introduction

In the World Health Organization's Global Strategy on Digital Health, digital health is described as “the field of knowledge and practice associated with any aspect of adopting digital technologies to improve health, from inception to operation” (WHO, 2020). Within the field of health psychology, there has been an enormous increase in behaviour change interventions that use digital technology (Crutzen et al., 2018). To change behaviour, it is crucial to be aware of Lewin’s formula indicating that behaviour (B) is a function of a person (P) and his or her environment (E): $B=f(P,E)$ (Lewin, 1936). In other words, digital technology should not only be used to target behaviour directly, but should also take the person and the environment in which the behavior takes place into account. The first step in doing so, is by using opportunities provided by digital technology to measure all three elements of this formula.

Technological possibilities to measure behaviour (B) are improving constantly. For example, physical activity and sleeping are behaviours that can be measured unobtrusively by means of mobile phones and watches, and online behaviour can be easily tracked (e.g., how people navigate through the Internet and what content they pay attention to (Skinner et al., 2017)). There are also possibilities with existing technologies in terms of capturing aspects of the environment (E). Mobile phones, for example, can track location. Measuring the person (P) is much more complicated, because we cannot directly measure people's cognitions or other psychological constructs. For now, we have to rely on indirect measures, such as reaction times and answers to questions.

Answering questions and providing tailored feedback based on the answers provided by participants is the key working mechanism when using computer-tailoring in behaviour change interventions (De Vries & Brug, 1999; Hawkins et al., 2008). This behaviour change method has proven to be (cost-)effective and results in participants being exposed to material that is tailored to their social-cognitive profile (Krebs et al., 2010; Noar et al., 2007; Smit et al., 2013; Wolfenden et al., 2015). At the same time, answering questions to assess this profile increases participant burden, which might contribute to low levels of engagement and high attrition - key challenges in digital health (Kohl et al., 2013; Short et al., 2018).

The topic of this article concerns novel possibilities for measuring psychological constructs related to the person. Whereas items in questionnaires are commonly used operationalisations that utilise natural language, other proxies might be more appropriate for linguistically diverse test takers. Moreover, these other proxies might reduce participant burden and as a result improve engagement and lower attrition, because it is not needed anymore to complete lengthy questionnaires. This may ultimately increase the impact of digital behaviour change interventions using computer-tailoring (Glasgow et al., 2006; Yardley et al., 2016). Therefore, the aim of this article is to provide insight into how routinely collected data and novel self-assessment methods can be used in computer-tailoring to measure psychological constructs and address key challenges in digital health (e.g., participant burden, engagement, attrition).

Trends in assessment of psychological constructs in computer-tailored interventions

Over 360 computer-tailoring studies have been conducted to date by researchers across health and computer sciences (Ghalibaf et al., 2019). Psychological constructs have been measured in approximately 60% of these studies, predominantly via questionnaires (91%), diaries or other written records (8%) (Ghalibaf et al., 2019). These psychological constructs can then also be used for tailoring purposes.

Selection of tailoring variables covering psychological constructs has typically been based on underlying theories guiding the intervention development. The Transtheoretical Model (Prochaska & Velicer, 1997), Social Cognitive Theory (Bandura, 1986), the Health Belief Model (Rosenstock, 1974) and the Reasoned Action Approach (Fishbein & Ajzen, 2010) have been the most commonly used theories (Ghalibaf et al., 2019). Resultantly, constructs like stage of change, self-efficacy, perceived benefits and barriers, and goals have been some of the most commonly used tailoring variables (Broekhuizen et al., 2012; see supplementary material).

More recently, there has been increasing recognition of the need to expand the theoretical basis of behaviour change interventions to address a broader set of behaviour change determinants (e.g., habits, affect) (O'Carroll, 2020; Rhodes et al., 2019), as well as determinants likely to impact on how people process intervention content (e.g., need for cognition) (Nikoloudakis et al., 2018; Smit, Linn, et al., 2015). In addition to this, there is growing criticism of the static nature of the theories cited above, with critics arguing they do not apply as well to behaviours that require ongoing participation (e.g., physical activity and healthy eating) as they do for limited occurrence health behaviours (e.g., health screening; Dunton, 2017). This has led to growing advocacy for considering application of these theories in the context of how determinants of behaviour may vary over-time and across situations (Chevance et al., 2020; Duckworth et al., 2016; Millar, 2017).

While the types of tailoring variables that have been used in interventions have been generally well reported, detailed information about how tailoring variables have been measured (e.g., number and content of items, response scales, psychometric properties) has not been as transparent, or heavily scrutinized in the literature (compared to outcome assessments for example). Anecdotally, the use of shorter measures has become more common as interventionists have tried to provide iterative feedback over time (requiring multiple assessments), and have moved from print and web-based delivery modes to mobile phones. Completing long questionnaires on mobile phones presents usability issues, and fails to capitalise on the advantages of real-time assessments that mobile devices can provide. Regardless of the degree of iterativity and the delivery modes used, though, greater attention should be paid to measurement of psychological constructs in computer-tailored interventions. This concerns both commonly used approaches and novel possibilities. Without sufficient information about the input used for tailoring, it is hard to gain more insight into whether tailoring output consists of relevant and well tailored messages.

Measurement as a fundamental issue

The latter touches upon a fundamental issue in psychology and related fields, including health psychology, health communication and behavior change science, as measurement of psychological constructs suffers from severe problems. That is, validated questionnaires often violate conditions required for validity (Hussey & Hughes, 2020). Fried (2017), for example, shows how commonly used 'validated' depression scales measure different aspects of depression. Also, results from typical psychometric analyses are not informative regarding an instrument’s validity (Maul, 2017). For example, use of such analyses may fall short of providing rigorous, potentially falsifying tests of relevant hypotheses. Some of these underlying problems, specifically applied to explaining behaviour in behaviour change science, have been explained elsewhere in more detail (Peters & Crutzen, 2017). In short, most theories in psychology are lax when it comes to accuracy and precision of their definitions and operationalizations. This causes problems such as those identified in the aptly named article “The confounded self-efficacy construct” (Williams & Rhodes, 2016) and in the article by Fried (2017) cited earlier: researchers use terms such as ‘attitude’, ‘habit’, and ‘intrinsic motivation’ without having a sufficiently accurate definition to accompany that label, let alone rigorous and comprehensively developed instructions for how to develop measurement instruments for those constructs.

On the one hand, this means that there is a fundamental issue that needs to be solved. On the other hand, psychology in general, and health psychology, health communication and behavior change science more specifically, is applied to target (health) problems that cannot wait for this. So, the science of behaviour change needs to move simultaneously ‘slow’ and ‘fast’ (cf. Armitage, 2015). ‘Slow’ in the sense of working towards solutions to address underlying problems of measurement in psychology, such as unequivocal definition and measurement of psychological constructs without the need for central curation and oversight (Peters, 2020). ‘Fast’ in the sense that behavior change interventions will be developed meanwhile, as there is a pressing need to reduce morbidity and mortality related to human behaviour (Ritchie & Roser, 2019). This article focuses on the latter; how can we reduce participant burden, and subsequently increase engagement and reduce attrition, in currently developed behavior change interventions. More specifically, how can we do this by using novel possibilities for measuring psychological constructs.

Novel possibilities for measuring psychological constructs in computer-tailored interventions

If we look at possibilities to measure psychological constructs, then they can be presented in a variety of dimensions that reflect an underlying continuity (Peters & Crutzen, 2017). Looking at the dimension of drivenness, for example, on the one hand of the spectrum there is the use of questionnaires to assess psychological constructs and provide feedback based on the pre-specified tailoring rules. These rules are expert-driven (e.g., informed by theory or another rationale intervention developers have in mind), meaning that the rules are specified in advance. In current practice, the participant burden of expert-driven questionnaires is high because of the need to complete relatively long questionnaires. On the other hand of the spectrum there is, for example, the possibility to infer psychological constructs based on routinely collected data on online behaviour (e.g., Likes on Facebook; Kosinski et al., 2014). With routinely collected data, inferences are made based on a data-driven approach. As a result, the participant burden is relatively low given that no active contribution from the participant is needed. In short, drivenness (expert-data), and participant burden (high-low) are two dimensions on which possibilities for measuring psychological constructs vary. In the following, we will describe the possibilities to reduce participant burden, both applying a data-driven approach using routinely collected data and applying an expert-driven approach using purposively sampled data, yet using novel methodologies to reduce the associated high participant burden.

Deriving information about psychological constructs using routinely collected data

Devices and sensors are increasingly used in all aspects of everyday life and the amount of data that is generated and available for profiling users is staggering. The International Data Corporation estimated that there will be more than 59 zettabytes of data created and captured in 2020, with current trends suggesting the amount of data will double every four years (IDC, 2020). Undeniably, it is already common practice to utilise this data for audience segmentation. Companies like Google and Facebook, for example, facilitate targeted advertising by tracking what articles people read, recent purchases they have made, and even the content of their private emails and messages. Implicit in this approach is that they can obtain proxy measures of the person in terms of interests, desires and needs, and thus increase advertising efficacy by targeting those most susceptible or likely to find the advertisement relevant (Bidargaddi et al., 2017).

Analogous efforts to derive information about the person using routinely collected data are underway in psychiatry and personality psychology (Azucar et al., 2018; Bidargaddi et al., 2017). As with computer-tailoring, measurement of mental health symptoms and personality have traditionally been collected using questionnaires. For the field of psychiatry, utilising routinely collected data offers the potential to collect more temporally valid assessments of mood and symptom severity, and thus potentially offer more timely and targeted interventions. For example, a pilot study that tracked patients with bipolar disorder over twelve months found that clinical symptoms were related to objective smartphone measurements. More specifically, cell tower movements and call logs, which were described as proxy measures for physical activity and social communication, respectively (Beiwinkel et al., 2016). For the field of personality psychology, assessments utilising routinely collected data may also have public health benefits (e.g., tailoring health interventions to increase adoption and user experience). Although this area of research is still relatively young, many studies have been conducted investigating associations between online social media behaviours (e.g., using digital footprints such as likes, language used, pictures) and personality. A recent meta-analysis of 16 studies suggested that the overall strength of association (i.e., meta-analytic correlations) between automatically collected social media data and the big five personality traits ranges from 0.29 (agreeableness) to 0.40 (extraversion), which is in line with standard "correlational upper limits" for behaviour to predict personality (Azucar et al., 2018). As the strength of the association was improved when multiple digital footprints were included versus the use of a single type of digital footprint, the authors were optimistic that precision would improve as the field progresses and access to large datasets evolves.

These examples raise the question of how routinely collected data could be used in the context of delivering computer-tailored behaviour change interventions. Given the widespread use of audience segmentation commercially, one obvious application could be the identification of people who could benefit from an intervention (e.g., those with low mood in case of a mental health intervention). Given the popularity of social media platforms, targeting interventions based on social media footprints could significantly increase the reach of computer-tailored interventions, including reaching those who are not yet contemplating behavioural changes but may benefit from doing so based on their digital footprint. It also seems possible that at least some constructs that are typically assessed in order to provide tailored information could be approximated from routinely collected data. For example, it may be possible to deduce exercise habits using a smartphone by combining automatically collected data on behaviour frequency (e.g., using accelerometry, gps or movements between cell towers) with data on contextual cues (e.g., location, time of day, interactions with specific people). Likewise, constructs like intentions, attitudes and need for cognition could possibly be assessed based on browser history, focusing not just on what people click on, but what they avoid or do not attend to. To illustrate, if people's browser history shows web pages that mainly consist of (text accompanied with) pictures to take a relatively greater share than web pages with text only, this might be indicative of a lower rather than greater need for cognition (which might also be associated with, for example, educational level or age (Bruinsma & Crutzen, 2018)). This type of behavioural data might be particularly amenable to assessing aspects of psychological profiles that are less reflective in nature, such as implicit attitudes - a construct that is now usually measured by Implicit Association Tests (O'Shea & Wiers, 2020). While data collection is now relatively straight-forward, the intellectual challenge lies in considering how to model such high-definition data and derive meaningful summary statistics. In the context of developing proxy measures for computer-tailoring, this should be driven, at least in part, by specific scientific questions and hypotheses. This is equally true for purposively sampled data.

Deriving information about psychological constructs using purposively sampled data

This section explores methods of purposively assessing tailoring variables that move beyond the traditional questionnaires by developing questionnaires that are individually tailored in terms of content and length (e.g., applying computer-adaptive testing (CAT) methodology) or move towards more interactive multimedia-based approaches that entirely replace questionnaires (e.g., the use of images and serious games [i.e., games designed for a primary purpose other than pure entertainment]). While tailoring rules based on purposively sampled data remain expert-driven, the associated participant burden is much lower; something we will further illustrate in the following section using the three examples mentioned.

To briefly talk about developing individually tailored questionnaires first. When applying CAT, each questionnaire item is dynamically selected from a pool of items based on a measurement model (Smits et al., 2011). This results in a shorter questionnaire that is optimized for a specific individual and contains only items most likely to be relevant (e.g., most salient beliefs) for this particular person. This way, the questionnaire that serves as input for computer-tailored feedback becomes tailored in both length and content for each individual user. When applying CAT to mental health measurement, it was found that questionnaires can be reduced in length to one-third of the initial number of items (Smits et al., 2011). To the best of our knowledge, however, CAT has not yet been used in the context of computer-tailoring.

Second, the interest in serious games as assessment tools has been steadily increasing over the last several years in the domains of education, health, government and industry (Kato & De Klerk, 2017). This is owing to the perception that serious games can both promote user engagement (e.g., through interaction and multisensory environments) and provide more ecologically valid assessments, especially of skills and competencies (e.g., by measuring game behaviours that represent reactions, planning and prioritisation in real-time and "real like" environments) (De Klerk & Kato, 2017). For example, the game CancerSpace presents players (i.e., healthcare professionals) with real-world situations in which they must make care decisions similar to as they would in clinical practice. The game includes a number of interactions with patients in which the player must try to educate the patient and persuade him or her to undertake screening, thus providing insight into their knowledge, communication and problem solving skills (Swarz et al., 2010). A rising number of serious games have also been designed to both assess and train a person's cognitive functioning. The product BrainTagger, for example, has been designed to screen for delirium in older emergency patients. Each game is linked to a standard psychological task and its associated cognitive function (e.g., response inhibition) (Zhang & Chignell, 2020). In a similar vein, games have also been used to deliver cognitive bias modification training and assessment tasks online, with several already evaluated in the behaviour change field (Jayasinghe et al., 2020) and some commercial products widely available via app stores (Zhang et al., 2018).

As with the use of routinely collected data for assessment, the expertise required for advancing purposively collected game-based data for assessments is advancing but is still under development. In the game CancerSpace for example, the player's conversation choices are evaluated using pre-programmed decision trees (Swarz et al., 2010). This is akin to the expert-driven rules used in traditional computer-tailoring interventions. Whereas in BrainTagger, machine learning is used to adjust cognitive assessment scores by comparing differences in game parameters across tasks and individuals applying a data-driven approach. Establishing validity and the cost-benefit of using these assessment methods are additional key challenges (see Discussion section).

A lower hanging fruit may be the adoption of game-based elements into more traditional forms of assessment. For example, the use of avatar selection may be an engaging way to examine user self-perceptions, both real and ideal. This method would also lend itself to tailoring to a user profile (i.e., considering how elements of the person cluster together). A simplified example of how this approach could be utilised in a low cost way is highlighted in Text box 1.

To inform avatar development in an evidence-based way, or really, any profile-based tailoring method, person-based data collected from previous computer-tailoring studies could be examined for clusters. Identified clusters could then form the basis for avatars. For example, cluster analysis with data from 753 smokers who participated in an effectiveness trial of a web-based, computer-tailored smoking cessation programme based on smokers' baseline scores for pros and cons of quitting and quitting self-efficacy showed that among smokers in the preparation stage of change (i.e. motivated to quit smoking within one month), four clusters could be identified; Classic, Unprepared, Progressing and Disengaged Preparers (Smit et al., 2018). These clusters significantly differed with respect to all clustering variables, their gender, cigarette dependence and educational level. Most importantly, results suggest that smoking cessation interventions tailored to the preparation stage of change, i.e. the set of cognitions usually present in preparers, are only appropriate for the subgroup we defined as Classic Preparers. The other clusters might need different interventions as they display a different cognitive profile. Similarly, in a computer-tailoring intervention targeting post-treatment breast cancer survivors (Short et al., 2017), over 400 participants completed baseline and follow-up measures of psychological constructs, demographics and health status information using standard questionnaire items. This data could be used to examine how these variables cluster together, and importantly if clusters are related to intervention responsiveness and unmet needs. If so, tailoring based on these clusters in a future iteration of the intervention could be advantageous. Importantly this would reduce the burden associated with developing hundreds of iterations of intervention messages and may reduce 'tailoring waste' - i.e., message permutations that are developed but rarely delivered, or do little to increase relevance of information. By allowing users to select an avatar that corresponds to an evidence-based cluster, the burden of assessment could also be greatly reduced. Avatar-based tailoring will necessitate examining the extent to which avatar self-identification relates to current or ideal self-perceptions, and the extent to which this can be manipulated with intervention instructions. If both are achievable, avatars might have the added advantage of providing insights into discrepancies of self that the user would like to change (Klimmt et al., 2009; Meijer et al., 2020). Future research examining the utility of an avatar-based approach is therefore highly encouraged.

A third approach that could be considered is the replacement of standard questionnaire items with visual representations. This method has already gained traction in personality assessment, owing predominantly to perceptions that this approach can enhance engagement, reduce test taker fatigue (by requiring less attention to process), and may result in shorter test batteries due to the ability of images to provoke stronger reactions than text (Leutner et al., 2017; Meissner & Rothermund, 2015). There is some evidence to support these perceptions (e.g., Leutner et al., 2017), though as with all of the discussed methods validity still needs to be established. Research into the perceptions of these measures will also be needed.

Assessment

To generate your avatar, please select which of the following images in each category best represents you over the last month in relation to your physical activity?

Construct	Intention	Self-efficacy	Social support
Image options	*Avatar proudly wears goal and commitment badge (high)*	*Avatar is bounding over medium size hurdle (high)*	*Avatar surrounded by entourage (high)*
	Avatar is chilling out and a badge is collecting dust on the floor (low)	*Avatar is looking dwarfed by the hurdle (low)*	*Avatar is standing on its own (low)*

Tailoring to profile

Based on the choices made, the user will end up with 1 out of 8 possible avatars. The avatars can be used to generate computer-tailored feedback based on the three psychological constructs measured by creating the avatar.

Intention	Self-efficacy	Social support	Avatar profile
High	High	High	'You are set for success!'
High	High	Low	'You are almost ready for success, but let's ensure some more social support!'
High	Low	High	'You are almost ready for success, but let's get you some more confidence!'
High	Low	Low	'Your motivation is great, so let's ensure some social support and increase your confidence too!'
Low	High	High	'You are almost ready for success, but let's ensure you're sufficiently motivated!'
Low	High	Low	'Your confidence is great, so let's ensure you're sufficiently motivated and will receive some social support too!'
Low	Low	High	'Your social support is great, so let's ensure you're sufficiently motivated and increase your confidence too!'
Low	Low	Low	'Before making any changes to your physical activity, let's work on your motivation, confidence and social support!'

It is possible that the measures discussed in this section may be perceived as less trustworthy or credible than standard questionnaire-based approaches. Based on models of user experience and engagement (Crutzen et al., 2011; Short et al., 2015), this would lead to an increased likelihood of non usage of the intervention. On the flip side, if the measures are experienced as fun, or assessments lead to a greater sense of novelty or being more deeply understood, greater engagement could be expected.

Discussion

This article provides insight into how routinely collected data and novel self-assessment methods may be used in computer-tailoring to address key challenges in digital health (e.g., high participant burden, low engagement, high attrition). The examples presented from the literature (e.g., Swarz et al., 2010; Zhang & Chignell, 2020), and from our own creative efforts suggest that the development of novel proxy measures for measuring psychological constructs relevant to computer-tailoring is indeed possible. However, the extent to which these measures are valid and actually do reduce participant burden, increase engagement and have other potential benefits (e.g., facilitating profile-based tailoring) is speculative and needs further investigation. It also needs to be acknowledged that both scientific reasoning and creative efforts are needed to develop novel possibilities of measuring psychological constructs in computer-tailored interventions. Based on what has been achieved to date, and our own efforts in developing examples, it seems some psychological constructs (e.g., mood, personality) may be easier to capture and distinguish from other constructs than others (e.g., self-efficacy, social support). Our avatar example is one attempt to address this issue. The extent to which this approach actually does capture aspects of the person in a meaningful way that can be used for computer-tailoring also needs further investigation. It is hoped that this article serves as a stimulance for driving further momentum in this area. To this end, we next discuss some additional challenges to consider and describe recommendations for future research and practice.

Challenges of using novel possibilities for measurement

One of the advantages of utilising standard self-report questionnaires to measure psychological constructs for computer-tailoring is the simplicity of assessment. The background knowledge and skills to administer and interpret these standard assessments are also typically well aligned with the discipline expertise of those developing behaviour change interventions. Whereas, simplicity of collection and having the required expertise is less likely to be the case when drawing on routinely collected data and moving beyond standard self-report questionnaires.

When it concerns routinely collected data, first of all, data compilation can be complicated. Services and apps that collect data of interest are often owned and operated by businesses and therefore sit outside of mainstream health care and research. Second, where mainstream health data are available they are often in multiple silos. To fully capitalise on routinely collected data the ability to aggregate personal data sets from these sources will be necessary (Bidargaddi et al., 2017). Advanced technical and modelling expertise will also likely be needed. While the formation of multi-disciplinary teams is generally considered a pro, especially in the context of solving complex problems, working in such teams presents new challenges (e.g., overcoming field specific jargon) and sufficient time and willingness is needed to build a productive working relationship. Moreover, the ethical, legal, and social landscape varies, depending upon the domain (e.g., clinical, research, government) in which routinely collected data are used. The businesses that collect data and have expertise in person-based assessment may have lower ethical standards than what would be accepted in health and medical research and service delivery (Bidargaddi et al., 2017). For example, personal characteristics intuited from social media data (i.e., characteristics not explicitly disclosed by individuals) have already been used to target political propaganda prior to elections (Cadwalladr, 2017), and the availability of strategies for identifying individuals based on vulnerable emotional states has already been communicated to advertisers (Levin, 2017). While the prospect of being able to target individuals who may benefit from a behaviour change intervention is exciting and could expand the reach of public health initiatives, the dangers associated with misuse should be carefully considered and managed. Therefore, across all domains, development and implementation of guidelines and best practices is helpful and we will elaborate upon this in the next section (using ethical guidelines for COVID-19 tracing apps as an example).

Similarly, the expertise that is required to purposively collect - and subsequently interpret - data through, for instance, game-based assessment methods (e.g., the avatar example we provided), is still under development. While current applications make use of both expert-driven decision trees (Swarz et al., 2010) and user-driven machine learning (Zhang & Chignell, 2020), the validity of these approaches may be compromised by engagement mechanics that are irrelevant to assessing the construct and thereby introduce additional error or noise (Kato & De Klerk, 2017). This has been proposed as a possible reason as to why gamified cognitive bias modification tasks have mixed findings (Boendermaker et al., 2016). Moreover, the development of game-based assessment methods as part of more traditional forms of assessment is also likely to bring about relatively high costs, which makes these novel assessment forms unlikely to be cost-effectiveness unless they are much more effective in reducing participant burden, increasing engagement, reducing attrition and as such ultimately increasing the effectiveness of computer-tailored health interventions, than the traditional assessment methods currently employed. With this issue of cost-effectiveness, however, come the challenges of defining the best outcome measure that can compare interventions across health behaviours, but is also sensitive to behaviour-specific changes resulting from the intervention, and of determining what increase in effects is required to justify the investments needed (Smit, De Vries, et al., 2015). This raises questions about whether metrics related to participant burden and intervention engagement and attrition would be sufficiently informative for the policy makers that are responsible for allocating limited funds and willingness to pay for each unit of effect when it concerns reducing participant burden, increasing engagement and/or decreasing attrition.

Recommendations for future research and practice

Whereas the examples presented in this article do suggest that routinely collected data and novel self-assessment methods may be useful for assessing psychological constructs relevant to computer-tailoring, the extent to which these measures are valid and actually do reduce participant burden, increase engagement, reduce attrition and have other potential benefits (e.g., facilitating profile-based tailoring) is speculative and needs further investigation. One of the most obvious steps to take is to compare the proposed assessment methods with traditional methods (e.g., a self-administered questionnaire). Whether such comparative attempts are, however, truly valuable is a concern the scientific community should be reflective about, as - as indicated before - even commonly-used questionnaires that would serve as comparison often violate conditions required for validity (Hussey & Hughes, 2020) and results from typical psychometric analyses may not be informative regarding an instrument's validity (Maul, 2017).

At the same time, however, there is the need to move 'fast' in the sense that digital behavior change interventions need to be developed with a reduced participant burden, increased engagement rates, reduced attrition and a wider reach, as there is a pressing need to reduce morbidity and mortality related to human behaviour (Ritchie & Roser, 2019). To establish whether the routinely collected data and novel self-assessment methods described in this article are able to respond to this need, future research efforts are required that focus on participants' perceived burden of completing the different measures and their engagement with the interventions that these measures are a part of. To illustrate this based on our avatar example, two versions of a computer-tailored intervention aimed at increasing physical activity may be created; one that includes the novel assessment method of self-efficacy and social support using the avatar and one that includes traditional questionnaire items pertaining to these two psychological constructs. Then, different approaches to research can be taken. For example, one may explore the time required to complete the different assessments and study participants' subjective experience regarding completion of the two assessments (e.g. in terms of perceived pleasantness and cognitive burden). Another example would be to assess intervention engagement after completion of various assessment methods. In both examples, specific attention could be paid to the linguistically diversity among test takers to provide evidence for the applicability of novel assessment methods across a broad range of possible intervention participants.

When it comes to recommendations for practice, one of the most pressing ones is the development and implementation of guidelines and best practices. A recent example are ethical guidelines for COVID-19 tracing apps (Morley et al., 2020). To be ethical, a contact-tracing app must abide by four principles: it must be necessary, proportional, scientifically valid and time-bound. These principles are derived from the European Convention on Human Rights, the International Covenant on Civil and Political Rights (ICCPR) and the United Nations Siracusa Principles, which specify the provisions in the ICCPR that limit how it can be applied. However, there are many ways in which an app can meet these principles. To address this gap, Morley et al. have synthesized 16 questions that designers, deployers and evaluators should answer. These questions are based on the principles mentioned above, but also how they translate into requirements (e.g., is it voluntary? does it require consent? is the purpose limited?). Transparency and informed consent are related to each other. When asking consent from participants in computer-tailoring, it should be explained that the intervention content provided to them (i.e. decision-making regarding content) depends on, for example, certain demographics and/or their social-cognitive profile (i.e. the logic behind it). In other words, the logic behind the decision-making should be explained (Crutzen et al., 2019). This raises questions about how to explain algorithm-based decisions to participants. We refer to Brkan (2018) for ways how to reconcile the potential recognition of the right to explanation with the transparency requirement. An important issue with data-driven approaches is that it can lead to new forms of discrimination in decision-making (e.g., based on gender or ethnicity). Such discriminatory consequences, however, can be mainly attributed to human bias and legal shortcomings. Therefore, suggested solutions include comprehensive auditing strategies, implementation of data protection legislation and transparency enhancing strategies (Favaretto et al., 2019).

Conclusion

Routinely collected data and novel self-assessment methods may be used in computer-tailoring to address key challenges in digital health (e.g., high participant burden, low engagement, high attrition), yet their application does not come without challenges. We have described how the proposed possibilities to measure psychological constructs may be used, as illustrated by concrete examples. The discussion of the challenges one may encounter when doing so and the recommendations for future research and practice are hoped to serve as a stimulance for driving further momentum in this area.

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Original Article

Using Ecological Momentary Assessment to Study Variations in Daily Experiences and Behaviors during the COVID-19 Pandemic

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Abstract

To stop the spread of the coronavirus disease (COVID-19), major restrictions to reduce social contacts have been introduced, which affect virtually all everyday behaviors including social relations. The main aim of the present study was to assess health as well as risk behaviors and COVID-19 related risk perception in a real-world setting, capturing daily variations and changes over time in the context of the COVID-19 pandemic, to understand how variations in risk perception relate to behaviors. Towards this end, during the first lockdown period of the COVID-19 pandemic in Germany (April to May 2020), a smartphone-based Ecological Momentary Assessment (EMA) was implemented including a final sample of N = 49 participants (73.5% female) recruited from the general population with a mean age of 29 years, ranging from 18 to 75 years. During the 14-day EMA period, health-related behaviors (i.e., eating and drinking behaviors, physical activity, sedentary behavior and overnight sleep), COVID-19-related risk behaviors (i.e., in-person social contacts and leaving home), as well as risk perception (i.e., likelihood of contracting COVID-19) were assessed at the end of each day for each participant. Daily assessment allows to conduct intraclass correlations and multilevel analyzes, to investigate both inter-individual (between-person) and intra-individual (within-person) variations. The data indicates that perceived likelihood of having contracted COVID-19 was significantly higher on days when participants had had more in-person social contacts and had left their homes for multiple reasons. Furthermore, there was substantial variation in health-related behaviors, including eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep not only between, but also within individuals. Overall, the data indicates relative accuracy in risk perception as participants acknowledged times of greater risk exposure. Moreover, although the first lockdown massively interrupted and restricted individual daily routines and habits, COVID-19-related risk as well as health-related behaviors showed marked short-time variations on a daily basis.

Introduction

The new emergence of the coronavirus disease (COVID-19) in 2019/2020 has caused a global pandemic with the death of hundreds of thousands of people and major disruptions to society and individual behaviors in daily life. To contain the spread of the virus, nationwide restrictions and lockdowns have been introduced asking people to stay at home, avoid in-person social contacts and follow strict hygiene behaviors as no medical treatment or vaccine was immediately available after the outbreak.

While nationwide restrictions and lockdowns help to reduce infection rates and to save lives (Fang et al., 2020), they have marked consequences for daily life behaviors. Fitness facilities, recreational sports and many food suppliers have been closed, hampering the engagement in physical activity and putting an additional burden on routine food-related behaviors. Early evidence suggests that widespread restrictions and changes in daily life during the COVID-19 pandemic have negatively impacted health-related behaviors, leading to lower levels of physical activity and increased sedentary behavior (Constandt et al., 2020; Fitbit, 2020), negative changes in eating behavior and dietary habits (Robinson et al., 2021), increased alcohol consumption (Ammar et al., 2020; Winstock et al., 2020), and a decrease in sleep quality (Blume et al., 2020). Thus, introducing restrictions and lockdowns to contain the spread of COVID-19 is also a challenge for general health and well-being of the population.

The course of the COVID-19 pandemic and public health policies not only affect behaviors but also our perception of the risk. Risk perceptions of adverse health outcomes have been examined as a motivational factor driving protective behaviors since the 1950s (Slovic, 1964). Since then, risk perception has become a key component of many theoretical frameworks for predicting and changing protective behaviors (Portnoy et al., 2014; Renner & Schwarzer, 2003; Weinstein, 2003). In general, these frameworks imply that perceiving a health risk for the self signals the need to take protective action (see also Finkel, 2008; Loewenstein et al., 2001; Menon et al., 2008; Renner et al., 2015; Slovic, 2000; Weber & Morris, 2010; Weinstein, 2003). Findings from prospective field studies conducted during acute epidemics (BSE, H1N1) provide empirical support for the behavior motivation hypothesis. Specifically, high perceived risk was associated with subsequent precautionary behavior (e.g., vaccination, hand sanitizer pick-up rate; Renner et al., 2007; Renner & Reuter, 2012; Reuter & Renner, 2011). Furthermore, a meta-analysis showed that heightening risk appraisals induced within experimental studies had effects of $d+ = .31$ ($k = 217$) and $d+ = .23$ ($k = 93$) on intention and behavior, respectively (Sheeran et al., 2014). A different facet of the risk perception-behavior relationship is addressed by the accuracy hypothesis, assuming that people who behave in a riskier way should also feel more at risk (Weinstein & Nicolich, 1993; Weinstein et al., 1998). Assessment of the risk perception-behavior relationship in the context of the COVID-19 pandemic is important considering the dynamic nature of pandemics (Ibuka et al., 2010; Lages et al., 2021). Ecological Momentary Assessments (EMA; Shiffman et al., 2008; Stone et al., 2007) or Ambulatory Assessments (AA; Trull & Ebner-Priemer, 2013, 2014) seem particularly well-suited to track daily variations and systematic changes over time with a high resolution. Up to date, there is a considerable gap in knowledge about the stability of risk perception and what factors drive changes in perceived risk (Lages et al., 2021; Siegrist, 2014). Investigating risk perceptions by using EMA enables research to capture possible dynamics in perceived risk on a daily basis and thus with high resolution, which will advance our understanding of the dynamics of risk perception.

The present study

The aim of the present study was to assess health-related as well as risk behaviors and risk perception in a real-world setting, capturing high-resolution data with daily variations and changes over time in the context of the COVID-19 pandemic. Towards this end, a smartphone-based EMA was implemented between the beginning of April and mid of May 2020 during the first lockdown period of the COVID-19 pandemic in Germany assessing daily health-related and risk behavior as well as risk perception across 14 days. Risk perception was assessed by the perceived likelihood of having contracted COVID-19 that day. Behavior was assessed with regard to COVID-19-related risk behaviors, i.e., leaving home and in-person social contact, and health-related behaviors, i.e., eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep. According to the accuracy hypothesis, we predicted a positive cross-sectional relationship between risk behaviors and risk perception. To control for the specificity of the effect, the relationship between health-related behaviors and risk perception was analyzed for comparison. The behavior motivation hypothesis was examined by time-lagged multilevel analyzes using risk perception as a predictor for behaviors on the following day. Finally, change over time in risk perceptions and behaviors were examined with particular focus on intra- and interindividual variation in order to determine effects between as well as within individuals.

Methods

Sample

Participants were recruited via the department online study platform of the University of Konstanz, social media postings (e.g., Facebook, Instagram) and email lists. Due to technical requirements of the application, only people with an Android smartphone (except Huawei due to compatibility problems) were eligible for participation. Out of 137 participants who filled in the baseline assessment, 52 participants started the EMA, of whom three were excluded due to low compliance (< 50% of days), resulting in a final sample of $N = 49$ (73.5% female). The sample had a mean age of 29.04 years ($SD = 13.50$, range = 18 - 75 years) with a great majority of participants being single (81.6%) and students or in training (77.6%). Overall, self-rated health status was good with an average of 4.43 on a 7 point Likert scale ($SD = 0.65$) with 45 participants (91.8%) reporting a 'very good' or 'good' health status. As compensation, participants had the choice between a 10€ voucher for local shops or donating the money to the COVID-19 emergency aid by the German Red Cross.

Procedure

Data was collected as part of the "EUCLID" project (https://euclid.dbvis.de/home) funded by the German Research Foundation (DFG FOR 2374), the Federal Ministry of Education and Research (BMBF 01EL1820A), and the Centre for the Advanced Study of Collective Behaviour (EXC 2117). The study was approved by the University of Konstanz ethics committee and carried out in accordance with the Declaration of Helsinki and the guidelines of the German Psychological Society. All participants gave informed consent prior to participation.

After completing an online baseline questionnaire about risk perception, protective behavior and future expected developments in regard to the COVID-19 pandemic (see the "EUCLID" project for further details, https://euclid.dbvis.de/home), participants were asked to install the study app (movisensXS, available on Google Play for Android) on their own smartphone and were sent an individual code to start the EMA. For the following 14 days, participants were asked to fill in a questionnaire on their smartphone at the end of the day about their risk perception, experiences and behaviors during the day. Assessment was possible starting at 6 p.m. each day, facilitated by individually timed reminders in the evening. EMA data was recorded from April 9 to May 18, 2020. At the beginning of the assessment, a lockdown was imposed on Germany, which was lifted towards the end of the study period as the epidemiological situation regarding COVID-19 improved (see Fig.1). Compliance during the EMA assessment was good with an average of 12.57 sampling days (*SD* = 1.96), ranging from seven to 14 days. After the EMA, participants were asked to fill in an online questionnaire similar to the baseline questionnaire at the beginning of the study.

Material and Measures

Health-related behavior

To assess health-related behaviors, participants were asked to report on their daily eating and drinking behaviors, i.e., healthy eating (portions of fruit/vegetables), unhealthy snacking (portions), alcohol consumption (number of 0.25l drinks), and the duration of physical activity (e.g., climbing stairs, going for a walk, sports; min), sedentary behavior (h) during the day and overnight sleep (h) during the last night. For the assessment, open scales with the respective unit were used.

COVID-19-related risk behavior

To assess risk behavior, the number of reasons for leaving home and in-person social contacts were

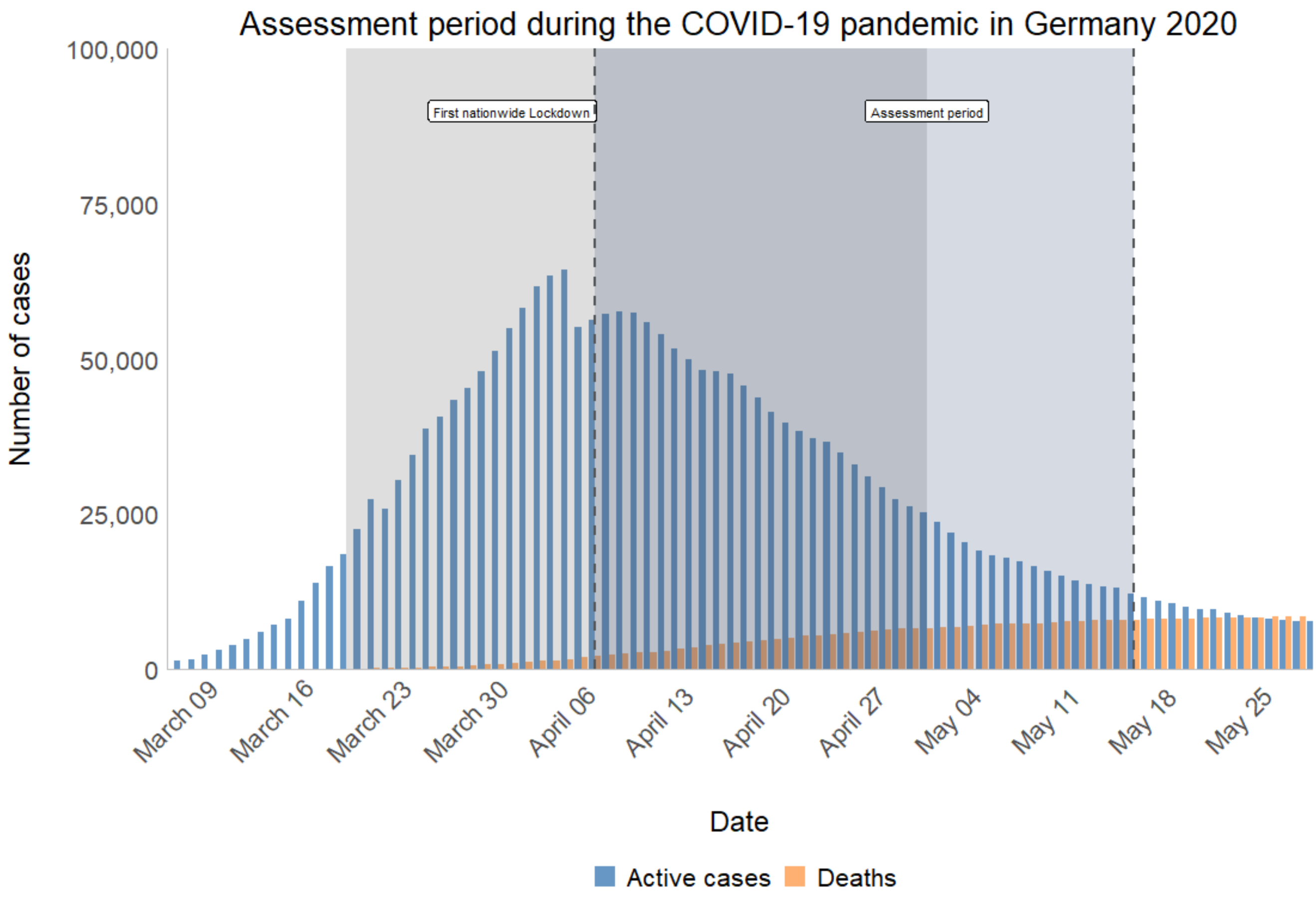


Figure 1. Epidemiological curve of COVID-19-related active cases and total deaths in spring 2020 in Germany. The grey area marks the first nationwide lockdown in Germany. The blue area between the dotted lines indicates the EMA period. Data source: Robert Koch Institute.

recorded. Participants were asked to indicate all reasons for leaving their home: (1) necessary grocery shopping or medical needs, (2) work, (3) physical activity outdoors, (4) visiting other people and/or (5) other reasons. In order to gauge the frequency of risk behaviors, the number of reasons for leaving home and in-person social contacts were recorded.

Risk perception

To assess daily risk perception, participants were asked to estimate how likely they were to have contracted COVID-19 that day on a visual slider ranging from (0) very low to (100) very high. The item was based on previous studies (see Brewer et al., 2007; Renner & Reuter, 2012; Weinstein et al., 2007).

Statistical analysis

For the statistical analysis, only data assessed during the EMA period was used, resulting in 616 assessment points that were included in the analysis. Variation between as well as within participants was analyzed using intraclass correlation coefficients (ICCs) and graphical depictions. Unrealistic values (> 24 h) in health-related behaviors and outliers in the number of in-person social contacts (> 11; n = 22), identified via boxplots (Tukey, 1977), were excluded.

Multilevel analyzes were performed to account for the hierarchical data structure with individual assessments (level 1) within participants (level 2). Intraclass correlations were used to assess inter- and intra-individual variation, indicating the proportion of variance, which results from differences between individuals as opposed to differences between assessments. Random intercept and random slopes models were computed and compared using a deviance test. Whereas random intercept models only include level differences between individuals, random slopes models estimate relationships for each individual, which can differ in magnitude and direction of the effect between individuals (Hox et al., 2010). Models that did not converge or indicated a singular fit were reduced as proposed by Bates et al. (2015) and Barr et al. (2013). If significant, pseudo-R-squares as proposed by Raudenbush and Bryk (2002) were computed for the preferred models. For random slope models, the proportion of negative relationships was additionally reported.

To investigate changes over time, models with a time effect, which was coded based on the dates of the EMA (range = 0 - 39), were tested. To assess the relationship between behaviors and risk perception, risk perception was used as a person-mean centered level 1 predictor (Enders & Tofighi, 2007). In order to predict behaviors on the subsequent day, a time-lagged variable for risk perception was used as a person-mean centered predictor.

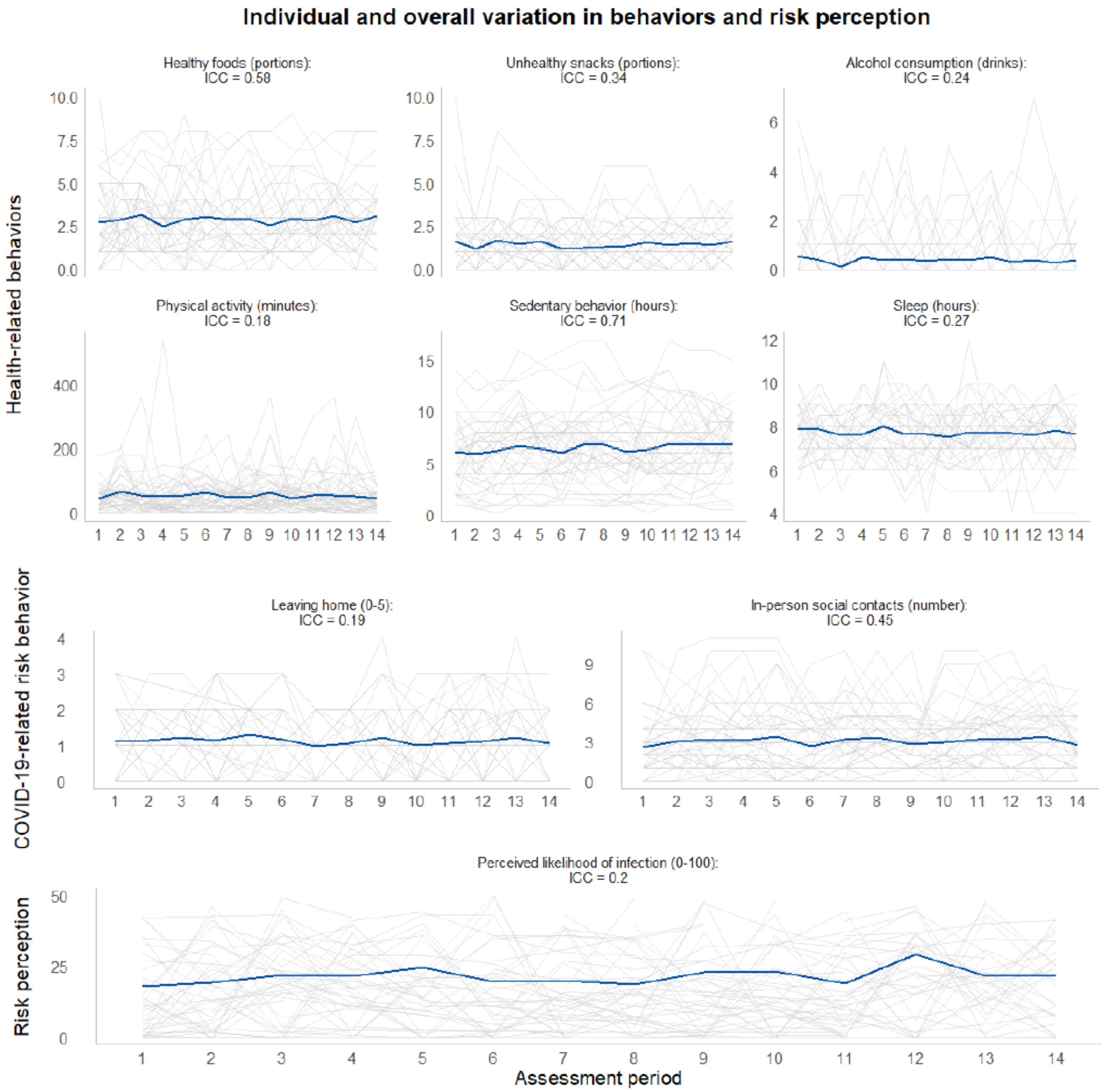
Multilevel analyzes were performed using R version 4.0.3 with the packages 'Ime4' (Bates et al., 2018), 'ImerTest' (Kuznetsova et al., 2018) and IBM SPSS statistics version 27 was used for the descriptive statistics.

Results

Variation and changes across the assessment period

Across participants, health-related behaviors including eating and drinking behaviors, as well as physical activity and overnight sleep were stable over time with only a slight increase in sedentary behavior per day (b = 0.06, t(601.62) = 3.56, p <. 001, pseudo-$R2$ = 0.02). However, substantial inter- and intra-individual variations were observed for all health-related behaviors. For a detailed overview of the descriptives and the variation within days but also between days of assessed health-related behaviors see Fig. 2.

Similar to health-related behaviors, COVID-19-related risk behaviors were stable over time, but



	Healthy foods (portions)	Unhealthy snacks (portions)	Alcohol consumption (drinks)	Physical activity (minutes)	Sedentary behavior (hours)	Overnight sleep (hours)	Leaving home (number of reasons)*	In-person social contacts (number)*	Perceived likelihood of infection (0-100)
n	616	616	616	615	612	615	607	594	616
M	2.86	1.43	0.36	54.10	6.46	7.69	1.46	3.40	21.56
SD	1.90	1.21	0.93	55.72	3.41	1.10	0.64	2.21	19.06

Figure 2. Variation in health-related behaviors, COVID-19-related risk behavior and risk perception. Grey lines indicate the variation of each participant, bold blue lines the average change over the course of the assessment period. *n* = number of observations. **M* and *SD* include only observations when participants had left their home/had in-person contacts.

varied substantially between as well as within individuals (see Fig. 2). Participants reported having in-person social contacts on average on 86.2% of the assessment days with on average 3.40 people (*SD* = 2.21) and a substantial range of 1 to 11. Furthermore, participants reported to have left their home on 75.3% of the assessment days (see Fig. 2 for details).

Nevertheless, participants reported a comparably low perceived likelihood of having contracted COVID-19 (*M* = 21.56, *SD* = 19.06). Even though active COVID-19 cases in Germany decreased over the assessment period (see Fig.1), this change was not reflected in a significant decrease in perceived risk (b = 0.24, t(401.68) = 1.68, p = .095). However, the ICCs indicated substantial inter- and intra-individual variation in risk perception (see Fig. 2).

Relationship between behavior and risk perception

Multilevel analyses was used to assess the relationship of behaviors and perceived risk. The results indicate that when people perceived their likelihood of having contracted COVID-19 on a given day as higher, they had left their home for more reasons (b = 0.02, t(45.04) = 9.71, p < .001, pseudo-$R2$ = 0.31, all random slopes positive) and had more in-person social contacts that day (b = 0.05, t(548.04) = 11.66, p < .001, pseudo-R2 = 0.20). Specifically, an increase of risk perception by 10 was associated with 0.2 more reasons of having left home and 0.5 more social contacts on the specific day. Although the magnitude of the relationship regarding leaving home varied between participants, it was positive for all participants.

Results also indicated that when people experienced a higher risk perception on a given day, they were more physically active (b = 0.41, t(566.12) = 3.32, p < .001, pseudo-$R2$ = 0.02) and had more alcoholic drinks (b = 0.01, t(568.06) = 3.68, p < .001, pseudo-$R2$ = 0.02) on that same day, although the effects were rather small. Specifically, an increase of risk perception by 10 was associated with 4.1 min more physical activity and 0.1 more alcoholic drinks on the specific day.

In addition, time-lagged multilevel analyzes revealed a significant but very small predictive effect of risk perception on the consumption of alcoholic drinks (b = 0.00, t(526.34) = 1.98, p <.05, pseudo-$R2$ = -0.03), which indicates that higher risk perception on one day was associated with small increases in alcohol consumption during the following day. However, no effect on other risk- or health-related behaviors occurred, indicating that risk perception was no predictor for most behaviors on the following day.

Discussion

The present study investigated daily COVID-19 risk perception and risk behaviors, as well as health-related behaviors during the beginning of the COVID-19 pandemic in Germany using a smartphone-based EMA across 14 days. The data shows substantial variation in risk perception and behaviors between as well as within individuals. In addition, data suggests that people accurately acknowledged greater risk-related behaviors in their risk perception on a given day.

The present study taps into a considerable research gap with major implications. The current COVID-19 pandemic represents the largest threat of a respiratory virus since the Spanish flu more than 100 years ago (Ferguson et al., 2020). High adoption rates of protective behaviors remain highly important to contain the spread of the disease and risk perception is known to be an important motivator for behavior change (e.g., Renner & Schupp, 2011; Sheeran et al., 2014). However, not much is known about the stability and dynamics of risk perception (Lages et al., 2021; Siegrist, 2014). This emphasizes the great need to investigate both the stability of perceived risk and what drives changes in risk perception, with a special focus on the COVID-19 pandemic. By using an EMA design, dynamics in risk perception can be investigated with the high resolution and with a focus on intra-individual changes, allowing to relate changes in risk perception to possible changes in behavior.

Accordingly, a main aim of the study was to understand how variations in risk perception relate to risk behaviors. The results of the present study suggest that participants draw on their own risk behaviors when gauging their personal risk. Specifically, the likelihood of having contracted COVID-19 was perceived to be higher on days when participants had more in-person social contacts or left their homes for multiple reasons. Although not directly related to risk, reasons for leaving home may be associated with a higher number of in-person social contacts (r = .32), thus being an indirect indicator of the risk of transmission. In addition, data showed that the positive risk perception-behavior relation was specific to those behaviors potentially increasing the risk of an infection and not a general effect across all behaviors. This finding resonates with previous research showing a positive association between risk behavior and risk perception, i.e., relative accuracy (Weinstein et al., 1998) across different risks (Brewer et al., 2004; Hay et al., 2007; Renner et al., 2008). However, the relation between perceived risk and risk behavior is complex as they influence each other continuously from day to day resulting in a dynamic interplay (Gerrard et al., 1996; Weinstein & Nicolich, 1993). Accordingly, repeated assessments are needed to investigate also the temporal dynamic and interplay of risk perception and risk behavior and describe changes and adaptive processes within individuals (i.e., adaptive accuracy; Renner et al., 2008; see also 'risk reappraisal'; Brewer et al., 2004). The present findings suggest that, during the COVID-19 pandemic, higher risk behavior was associated with increased risk perception, in the sense of relative accuracy. However, given that the current study did not track a full cycle of the pandemic, future studies should examine adaptive accuracy, focusing on the relationship between risk perception and risk behavior in the COVID-19 pandemic across an extended period of time to further assess the notion that risk perception measures relate to risk behavior and show relative accuracy.

The strict regulation of public life due to the COVID-19 pandemic has not only a large impact on social life; it also affects routine health-related behaviors. Evidence is emerging that restrictions on daily living such as social distancing and home confinement can have compromising effects on health-related behaviors such as physical activity and eating (Ammar et al., 2020). Using EMA across 14 days, the present study provides first insights into inter- and intra-individual variation of health-related behaviors. For instance, with the implementation of the lockdown in Germany, one may assume that one day is like the other, resulting in uniform appearance of health-related behaviors across time. To the contrary, as shown in Figure 2, there was substantial intra-individual variation across all behaviors assessed in the current study including eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep. Accordingly, at least for the present sample consisting of young adults and 77.6% of college students, health-related behaviors show considerable variability even during governmental regulation of social life. Future studies should expand EMA to reveal triggers for protective health-related behaviors, i.e., healthy eating and increased physical activity.

The present study revealed no significant deterioration in health-related behaviors over time. However, the study period may have been too short to reveal dynamic changes in health-related behaviors. The one exception was sedentary behavior which showed a slight increase over the assessment period. Even slight increases in sedentary behavior over an extended period may have significant health impacts (e.g., Ahmadi-

Abhari et al., 2017). Furthermore, while the overall effect for sedentary behavior was small, the ICC indicated that there are substantial differences between people. Thus, to further analyze compromising effects of the regulation of public life during pandemics, future studies may capitalize on the advantages of EMA to assess intra- and interindividual differences in health-related behaviors.

Using EMA allows to assess thoughts, feelings, behaviors, and environments in daily life to investigate how individuals feel, think, and behave in-the-moment (Geukes & Back, 2018), removing the problem of recall or memory biases (Garbinsky et al., 2014; Redelmeier & Kahneman, 1996; Robinson, 2014; Robinson et al., 2011) since the assessment takes place in the 'hot' moment of behavior or experience (Fahrenberg et al., 2007; Jezior et al., 1990). However, using EMA for health psychology research is also accompanied by some problematic issues that go beyond ethical concerns and privacy issues (Albrecht, 2016; Harari et al., 2016; Short et al., 2018). On the one hand, intensive assessment can be challenging for participants and might result in low compliance rates that can impede the accuracy of the measurement. However, recent data assessing in-the-moment eating behavior, a particularly complex and challenging behavior to assess (see e.g., Boushey et al., 2017; Rozin, 2007; Wahl et al., 2020), show that high adherence rates are possible, especially when using technical assistance such as reminder or addendum features (Ziesemer et al., 2020). On the other hand, intensive assessment can also challenge research to find new, elaborated methods of analyzing these high-dimensional data (Hamaker & Wichers, 2017; Short et al., 2018). An important achievement is therefore to develop methods that facilitate data analyzes beyond aggregated mean values and to consider the between- and within-person levels as illustrated in the present paper (for a promising approach, see Blumenschein et al., 2018, 2020; Debbeler et al., 2018; Wahl et al., 2020).

Furthermore, limitations of the present research need to be acknowledged. The present convenience sample is on average substantially younger (29.04 vs. 44.3 years of age, respectively) and includes more female participants (74% vs. 51%, respectively) than the German population. Furthermore, behaviors were self-reported, potentially including a social desirability bias (see e.g., Kristiansen & Harding, 1984) and the data assessment occurring on average around 8.39 pm and may have missed some behaviors, in particular with regard to nighttime drinking or snacking. Overall, the present findings on the dynamic of risk perception and health-related behaviors await replication based on representative samples and covering longer time periods.

Conclusion

The present findings provide first insights into risk perception, risk behaviors as well as health-related behaviors during the first wave of the COVID-19 pandemic in Germany. EMA allows to examine changes over time but also the interplay between risk perception and behaviors. This will advance our understanding of both the stability of risk perception and what drives changes in perceived risk, which will in turn reveal information that may be capitalized on by public health campaigns to increase protective behaviors. Specifically, the findings indicate that people accurately relate their risk perception to social behaviors potentially increasing the risk of an infection, but not to health-related behaviors in general. Furthermore, although the first lockdown massively interrupted and restricted daily routines and habits, COVID-19-related risk as well as health-related behaviors showed considerable intra- and inter-individual variability across the 14 days of recording. Overall, EMA is promising to determine the effects of a pandemic on risk perception and behaviors.

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Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Additional Information

Table A1. Temporal dynamics of risk perception, COVID-19-related risk behavior and health-related behaviors

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	*Pseudo-R^2*
Model 1: Perceived likelihood of infection											
Intercept	17.26	2.86	6.04	215.57	< .001	17.14	2.83	6.06	159.89	< .001	-
Time	0.24	0.15	1.68	401.68	.095	0.25	0.15	1.69	115.20	.093	
Model 2: Leaving home											
Intercept	1.17	0.13	9.21	210.87	< .001	NA	NA	NA	NA	NA	-
Time	-0.00	0.01	-0.47	396.18	.642	NA	NA	NA	NA	NA	
Model 3: In-person social contacts											
Intercept	2.90	0.37	7.76	191.60	< .001	NA	NA	NA	NA	NA	-
Time	0.01	0.02	0.69	580.44	.488	NA	NA	NA	NA	NA	
Model 4: Healthy foods											
Intercept	2.84	0.29	9.71	150.78	< .001	2.85	0.28	10.09	50.73	< .001	-
Time	-0.00	0.01	-0.05	615.90	.960	-0.00	0.01	-0.09	48.91	.929	
Model 5: Unhealthy snacks											
Intercept	1.46	0.19	7.78	221.21	< .001	NA	NA	NA	NA	NA	-
Time	-0.00	0.01	-0.31	555.86	.760	NA	NA	NA	NA	NA	
Model 6: Alcohol consumption											
Intercept	0.48	0.14	3.36	228.63	< .001	0.48	0.14	3.36	178.43	< .001	-
Time	-0.01	0.01	-1.02	470.27	.310	-0.01	0.01	-1.00	107.76	.320	
Model 7: Physical activity											
Intercept	59.66	8.33	7.16	214.73	< .001	NA	NA	NA	NA	NA	-
Time	-0.31	0.43	-0.72	388.44	.471	NA	NA	NA	NA	NA	
Model 8: Sedentary behavior											
Intercept	5.36	0.53	10.19	107.99	< .001	5.40	0.51	10.65	87.87	< .001	0.02[1]
Time	0.06	0.02	3.56	601.62	< .001	0.06	0.02	3.23	84.01	< .01	
Model 9: Overnight sleep											
Intercept	7.80	0.17	46.11	226.55	< .001	7.80	0.17	46.32	165.44	< .001	-
Time	-0.01	0.01	-0.77	494.16	.440	-0.01	0.01	-0.78	86.38	.438	

Notes. Models are not included if they did not converge or a singular fit was indicated. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

Table A2. Relationship between behavior and risk perception.

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	*Pseudo-R²*
Model 10: Leaving home											
Intercept	1.12	0.06	18.26	47.71	< .001	1.12	0.06	18.26	47.80	< .001	0.31[2]
Perceived likelihood of infection	0.02	0.00	13.66	557.23	< .001	0.02	0.00	9.71	45.04	< .001	
Model 11: In-person social contacts											
Intercept	3.14	0.25	12.69	48.27	< .001	NA	NA	NA	NA	NA	0.20[1]
Perceived likelihood of infection	0.05	0.00	11.66	548.04	< .001	NA	NA	NA	NA	NA	
Model 12: Healthy foods											
Intercept	2.83	0.21	13.43	49.16	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.66	567.17	.509	NA	NA	NA	NA	NA	
Model 13: Unhealthy snacks											
Intercept	1.42	0.11	13.13	49.47	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	0.65	567.54	.517	NA	NA	NA	NA	NA	
Model 14: Alcohol consumption											
Intercept	0.35	0.07	4.82	49.94	< .001	NA	NA	NA	NA	NA	0.02[1]
Perceived likelihood of infection	0.01	0.00	3.68	568.06	< .001	NA	NA	NA	NA	NA	
Model 15: Physical activity											
Intercept	54.37	3.97	13.71	48.88	< .001	NA	NA	NA	NA	NA	0.02[1]
Perceived likelihood of infection	0.41	0.12	3.32	566.12	< .001	NA	NA	NA	NA	NA	
Model 16: Sedentary behavior											
Intercept	6.47	0.42	15.42	48.86	< .001	6.47	0.42	15.42	48.87	< .001	-
Perceived likelihood of infection	-0.01	0.00	-1.87	562.90	.063	-0.01	0.01	-1.19	36.38	.242	
Model 17: Overnight sleep											
Intercept	7.69	0.09	85.93	49.08	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-1.18	566.20	.238	NA	NA	NA	NA	NA	

Notes. Models are not included if they did not converge or a singular fit was indicated. Predictors were centered on the person-mean. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

Table A3. Influence of perceived likelihood of infection on behaviors on the following day.

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	Pseudo-R^2
Model 18: Leaving home											
Intercept	1.11	0.06	18.69	46.88	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-1.36	515.71	.175	NA	NA	NA	NA	NA	
Model 19: In-person social contacts											
Intercept	3.09	0.23	13.24	48.13	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.84	502.97	.401	NA	NA	NA	NA	NA	
Model 20: Healthy foods											
Intercept	2.85	0.21	13.38	49.26	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	0.71	521.89	.480	NA	NA	NA	NA	NA	
Model 21: Unhealthy snacks											
Intercept	1.42	0.11	13.32	50.25	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.16	525.01	.871	NA	NA	NA	NA	NA	
Model 22: Alcohol consumption											
Intercept	0.35	0.07	4.82	50.23	< .001	NA	NA	NA	NA	NA	-0.03[1]
Perceived likelihood of infection	0.00	0.00	1.98	526.34	< .05	NA	NA	NA	NA	NA	
Model 23: Physical activity											
Intercept	54.19	4.09	13.27	48.67	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.06	0.12	-0.51	524.59	.612	NA	NA	NA	NA	NA	
Model 24: Sedentary behavior											
Intercept	6.51	0.42	15.38	48.81	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.59	516.67	.556	NA	NA	NA	NA	NA	
Model 25: Overnight sleep											
Intercept	7.69	0.09	85.03	49.26	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	1.87	523.75	.063	NA	NA	NA	NA	NA	

Notes. Models are not included if they did not converge or a singular fit was indicated. Predictors were centered on the person-mean. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

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Original Article

Just-in-time adaptive interventions in mobile physical activity interventions – A synthesis of frameworks and future directions

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Abstract

Mobile health (mHealth) solutions seem to be a promising approach to tackle sedentary lifestyle in modern society. They have the potential to identify situations when people are likely to engage in an unhealthy behaviour or when they face opportunities to perform healthy behaviours. These situations can serve as triggers to manipulate current behaviour, defined as just-in-time adaptive interventions (JITAIs) by using real-time behavioural data. The current position paper aims to provide a "think piece" by synthesizing evidence into a short conceptual overview of JITAI research by creating a framework and discussing future directions of JITAI research with a focus on PA interventions.

In conclusion, JITAIs are a promising feature in mHealth applications, however showing a lack of theoretical underpinning until today. To summarize evidence on JITAI implementation research and to provide some guidance, the following key features were identified: a JITAI should 1) correspond to real-time needs; 2) adapt to input data; 3) be system-triggered; 4) be goal-oriented; and 5) be customized to user preferences. These features aim to provide first insights into how to guide researchers and practitioners when developing and reporting JITAI features implemented in mHealth interventions. Concluding from the existing knowledge, the potential of machine learning and deep learning principles for JITAIs regarding mHealth should be further explored and established.

Introduction

Physical activity (PA) plays an important role in the prevention of noncommunicable diseases like cardiovascular diseases, diabetes and obesity (Penedo & Dahn, 2005). Levels of PA, however, are frequently found to be insufficient in modern society (Blair, 2009; Woll et al., 2011). Here, mobile Health (mHealth) interventions might be a promising approach to change PA behaviour and to reduce sedentary behaviour patterns (SBP) operationalized through minimal PA (i.e. PA of less than 1,5 MET) (Fiedler et al., 2020). Several key aspects have been shown to increase intervention efficacy when included in mHealth app development. One of these key components refers to the provision of behaviour change support in real time that is matched to when users are most capable of or in need of this support (Schembre et al., 2018). Various publications have used different terms to describe interventions that adapt the provision of support to an individual's changing internal and contextual state. Analogous to Hardeman and colleagues (2019) as well as Nahum-Shani and colleagues (2018), the term just-in-time adaptive intervention (JITAI) is used throughout this position paper, referring to the potential to immediately intervene in situations when people are either likely to engage in an unhealthy behaviour or when they face opportunities to perform healthy behaviours and adapt these interventions to tailoring variables (e.g. user preferences or sensor input).

The current position paper aims to a) summarize existing conceptualizations of JITAIs, to b) provide a comprehensive overview of JITAI features and mechanisms and to c) provide future directions concerning the implementation of JITAIs in mHealth research.

Theoretical foundations of JITAIs

In recent years, many widely used theories were adapted to explain within-person behavioural variability in order to support new technology-driven interventions that can adapt over time to a person's real-time behaviour and needs (e.g. the Dynamical System Model of Social Cognitive Theory; Martín et al., 2014). Since feedback as a self-regulating strategy is an important component of successful behaviour change, tailored just-in-time feedback depicts a key facet of JITAIs besides timeliness, goal-orientation, personalization and action-orientation (Schembre et al., 2018). In sum, theories indicate that feedback should be personalized, goal-oriented and that it should be presented when attention could be refocused to enhance the likelihood of goal attainment. Here, N-of-1 methodology can be insightful in order to evaluate individual trajectories and antecedents of behaviour change alongside JITAIs (Kwasnicka & Naughton, 2020; McDonald et al., 2017). Additionally, studies using ecological momentary assessments (EMAs), which are implemented to assess a desired outcome in a specific situation and the natural setting (Stone & Shiffman, 1994), grew rapidly during the past years (Reichert et al., 2020). The results of these studies can provide the foundation for more sophisticated JITAIs (Dunton, 2017; Spruijt-Metz & Nilsen, 2014) and for the application of advanced methods like machine learning algorithms (Kim et al., 2019; Maher et al., 2021; Rozet et al., 2019). By applying such algorithms, researchers aim to automatically detect meaningful patterns in behavioural data which is not feasible with pre-defined specifications due to the complexity and adaptivity of these patterns (Shalev-Shwartz & Ben-David, 2014).

Integration of JITAIs into mHealth interventions

With the continuously growing field of mHealth research and a high variety of different sensors and communication devices, the opportunities for the development and implementation of JITAIs are manifold (Reichert et al., 2020). JITAIs are especially useful for behavioural interventions to enhance PA and reduce SBP since they offer new types of timely and adaptive support in the users' natural environment. Therefore, bias due to retrospective measurement methods can be diminished and data of continuously measurements can be obtained. This is especially important as changing contexts (e.g. environmental factors) are highly associated with intervention effectiveness (Hardeman et al., 2019; Miller, 2019). Although a recent review points to the potential benefit of JITAIs as a key facet within mHealth intervention development (Fiedler et al., 2020), the current evidence on the effectiveness of JITAIs on PA and SBP is limited (Hardeman et al., 2019; Miller, 2019). Most existing JITAI studies show considerable methodological constraints regarding effectiveness measures, i.e. regarding sample size, study design and reporting of JITAI features. Due to the novelty of this research topic, most studies focus on feasibility rather than on the examination of effectiveness in order to aggregate basic knowledge about JITAIs. As an example for a study investigating effectiveness, the MyBehaviour study is interleaving machine learning mechanisms with multi-modal contextualised JITAI components (Rabbi et al., 2015). Here, automatically adapting PA and dietary behaviour advice was integrated into a smartphone application. In addition, PA energy expenditure was calculated and combined with caloric advice. Moreover, environmental information (location) was included for PA advice (Rabbi et al., 2015). Another example study is the SMARTFAMILY study which includes a JITAI (e.g. provide prompts) along with several other Behaviour Change Techniques (BCTs, e.g. provide information, goal setting, social support). Here, participants received a behavioural support message (i.e. push notification) if they were not sufficiently active (i.e. 100 steps or 2 minutes above 2 MET) during the past hour in order to reduce SBP and enhance PA (Wunsch et al., 2020). Thoroughly, existing studies point to a high acceptance of JITAIs by participants (Hardeman et al., 2019) and to an improvement of user engagement and adherence (Schembre et al., 2018). This, in turn, led to increased awareness of PA opportunities, increased PA and reduced time spent engaging in SBP (Hardeman et al., 2019) in participants using JITAI interventions as compared to no-JITAI users or no-intervention controls.

Theoretical conceptualization of JITAIs

In this position paper, three recent frameworks of JITAIs are presented and synthesized. Hardeman and colleagues (2019) defined three key features that define JITAIs: 1) the provision of behavioural support that directly corresponds to a need in real-time; 2) the adaptation of content or timing of support according to data collected by the corresponding input system since support was initiated; and 3) the system-triggered support. Nahum-Shani and colleagues (2018) distinguish between proximal outcomes (short term goals which can act as mediators to the distal outcome, e.g. daily step count or daily SBP periods), and distal outcomes (behavioural outcome of choice, e.g. increased PA level or decreased SBP level). These authors defined four key facets of JITAIs: 1) decision points (frequency of opportune moments to change the target behaviour and therefore the time at which an intervention decision is made); 2) intervention options (actions to be performed at a decision point); 3) tailoring variables (as obtained via active or passive assessments of individual information, determining intervention delivery); and 4) decision rules (link between the intervention options and the tailoring variables to provide the intervention at each decision point). Based on this conceptual framework, Gonul and colleagues (2019) additionally introduced machine learning strategies to individualize decision rules for intervention implementation (i.e. selecting BCTs) based on goal achievement.

Synthesis of theoretical foundations – A holistic and comprehensive conceptual framework for the implementation of JITAIs

As these above-mentioned conceptualizations (i.e. Gonul et al., 2019; Hardeman et al., 2019; Nahum-Shani et al., 2015) build upon different approaches (content, methodology), these conceptual frameworks are synthesized in the following paragraphs in order to provide a holistic and comprehensive overview of JITAI features and mechanisms.

Based on these frameworks, JITAI features were combined and synthesized, attaining a total of five factors which should be taken into account when constituting JITAIs for mHealth research: JITAIs should 1) correspond to real-time needs; 2) adapt to input data; 3) be system-triggered; 4) be goal-oriented; and 5) be customized to user preferences (see Figure 1). The former three factors are needed in order for an intervention to be defined as a JITAI intervention (Hardeman et al., 2019), whereas number 4) and 5) are additional factors which should be included whenever possible to enhance the likelihood of effectiveness and the quality of future interventions in terms of individual user-tailoring (i.e. personalized prevention / medicine). Subsequently, *Tailoring Variables* (e.g. GPS, sensor input data etc.) and *Decision Points and Rules* were added to the framework.

Hereafter, italic terms refer to Figure 1. *Theoretical implications* comprising of different *Antecedents of Behaviour* (e.g. mood, sleep, weather, location, opportunity for walking in green areas) and *Society / Policy Needs* determine the content of mHealth interventions. A special feature of such interventions are *JITAIs*, which use different information (i.e. *Tailoring Variables*) to compile a JITAI, e.g. data derived from a sensor, or user input data. Then, *Decision Points* are set in order to determine the points in time when a specific JITAI is triggered. The *Decision Rules* include the designation of principles like Timing (e.g. no JITAI at night), Frequency (e.g. no JITAI if another JITAI appeared just a couple of minutes ago), Duration (e.g. if a JITAI is ignored for a defined amount of time, it won't occur again for a given period of time), and BCT-related decision rules (e.g. if the BCT "comparison with others" is completed by the user, a JITAI appears). *User Input* (i.e. no Trigger during the next two hours) then lead to the decision if the JITAI is triggered and which *Trigger* will be executed. Beyond these detailed determinations, *Tailoring Variables and Decision Points and Rules* should finally be defined

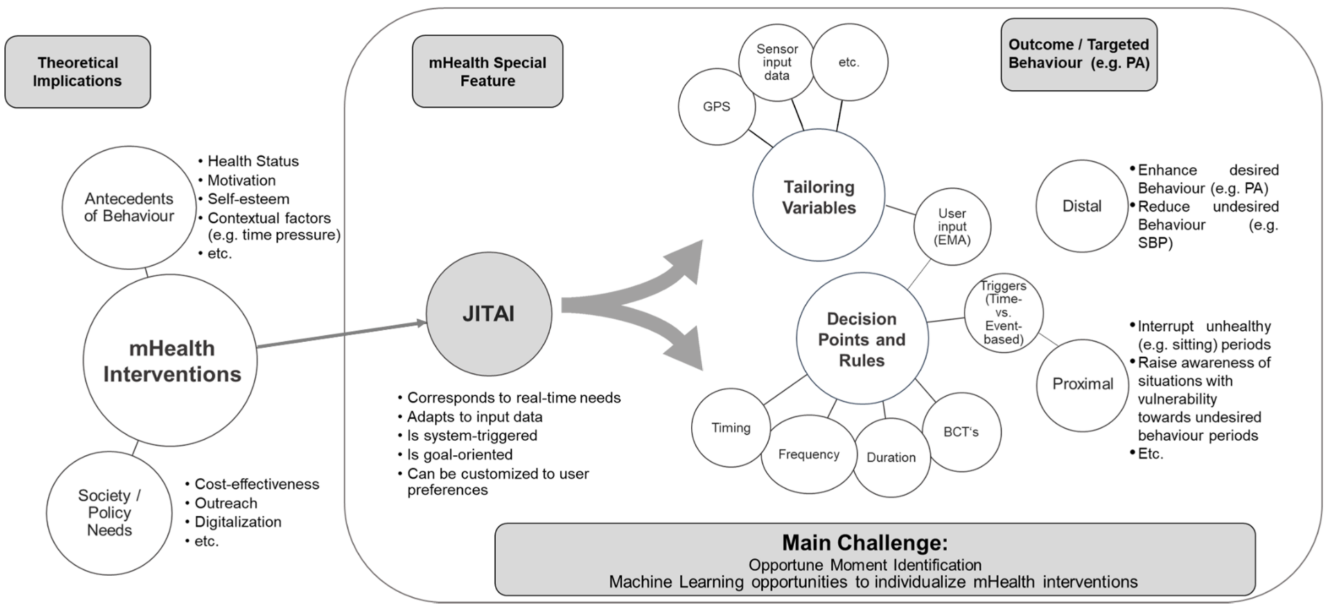

Figure 1. Conceptual framework of JITAIs.
On the left, this figure indicates the Theoretical Implications of mHealth for certain Outcome variables (on the right). Here, just-in-time adaptive interventions (JITAIs) as an mHealth Special Feature are described thoroughly concerning their key facets Tailoring Variables and Decision Points and Rules for Targeted Behaviour attainment. Note. PA: physical activity; SBP: sedentary behaviour pattern, BCTs: Behaviour Change Techniques, GPS: Global Positioning System; EMA: Ecological Momentary Assessments

in order to evaluate whether a *Proximal* goal (e.g. interruption of sitting time) is reached or not and to decide when an additional trigger is necessary and promising in order to reach a more *Distal* goal (i.e. long-term behaviour change).

In the following, an example for a mHealth application using a JITAI for the distal outcome to reduce SBP (which could be based on findings of a recent EMA study (Giurgiu et al., 2020)) by targeting the proximal outcome to interrupt inactive periods will be provided for a more comprehensive understanding of the interconnection of all facets. In a basic version, this JITAI is triggered if a) a connected sensor (e.g. an accelerometer) registers a prolonged period of a SBP (sensor input leading to a Decision Point) and if b) the user is not sleeping (e.g. it is not night-time), didn't receive a JITAI during the past 30 minutes, has not been sufficiently active on that day already (i.e. has already reached his or her step goal), and has no meeting or important appointment based on calendar entries (Decision Rules based on User Input and Tailoring Variables). If all Decision Rules are met at that certain Decision Point, the JITAI trigger will be sent in a moment where the user is likely to engage in an unhealthy behaviour and the intervention is promising for him / her to change this behaviour. This basic version could then be adapted according to user preferences and other variables (weather etc.) using machine learning principles.

Taken together, JITAIs aim to positively affect a *Targeted Behaviour*, i.e. PA or SBP based on well-aligned and user-specific adaptability. Setting up *Proximal* targets (i.e. short-term goals which can act as mediators to the *Distal* outcome) can help to achieve a long-term, i.e. Distal goal of enhancing PA and / or reducing SBP. Preliminary study results suggest that aiming at short-term goals, receiving feedback, targeting daily life activities as well as the explanation of the reason for reminders and triggers leads to a high acceptance of JITAIs by participants (Hardeman et al., 2019). Hence, implementing these features may improve user engagement and adherence and therefore enhance behaviour change (Schembre et al., 2018). Pilot and feasibility studies also revealed increased awareness of opportunities (e.g. to use active transportation opportunities), a reduction of SBP (e.g. to interrupt screen time periods) and enhanced PA levels, which underlines the potential of JITAIs to change health behaviours (Hardeman et al., 2019).

Opportunities and Challenges of implementing JITAIs in mHealth research

The implementation of JITAIs into mHealth interventions hold promising prospects for health behaviour change. Especially the ongoing development of more advanced and smaller devices to continuously and objectively assess PA and SBP (as well as other health-related variables) and the synthesis of gathered activity-data with additional sensory information (e.g. GPS, ECG, blood-sugar, etc.) further indicate the potential to adapt interventions individually to the user (Reichert et al., 2020).

However, the identification of *Decision Points and Rules* (i.e. *Opportune Moment Identification*) for behavioural support depicts the *Main Challenge* of implementing JITAIs (Gonul et al., 2019). Until today, the identification of the optimal number and timing of treatments generated by the JITAI, which are accepted by and effective for users, still remains unknown and most likely depends on the *Proximal* goal and the population of choice. Too frequently sent JITAIs within a specific context, such as the working environment or within school times, may lead to disengagement and/or low adherence and may increase the risk of intervention fatigue. With respect to the implementation of evaluation studies, researchers are advised to use conceptual foundations of JITAI research to determine the critical parameters and choices for participants which are most promising in various settings (e.g. concerning population, duration and aim of the study, and the *Targeted Behaviour*).

Additionally, there is still a need to construct personalized JITAIs comprising the inclusion of behaviour-related (e.g. inactivity) and context-related information (e.g. weather). Here, computational science and machine learning principles offer a new perspective to personalized mHealth interventions (Gonul et al., 2019). Machine learning strategies can include a variety of *Decision Points* into intervention development allowing for context-sensitive and therefore individually tailored and timely flexible support in contrast to fixed algorithms ("if then functions"). Automated system identification modelling can help to identify person-specific *Decision Points and Rules* referring to intrapersonal states and environmental conditions (Conroy et al., 2020). This allows for individually tailored feedback increasing the likelihood of high adherence, user acceptance and higher levels of PA compared to fixed conventional behavioural support. However, a precise forecast of individual behaviour based on system identification modelling requires an extensive data collection prior to intervention onset to gather training data sets derived from different sources and populations. This may impact cost-effectiveness and feasibility of study implementation within a given timeframe for researchers. Some technological aspects also need to be considered when implementing JITAIs into mHealth research, including a short durability of electronic devices due to battery requiring demands (e.g. geolocation features). Furthermore, the necessity of continuous wireless connection between sensors and mHealth devices have to be kept in mind for the development of JITAIs and mHealth interventions in general (Hardeman et al., 2019), as they potentially mitigate user satisfaction and are a source of missing data. Additionally, feasibility studies are warranted in target groups including persons without experience in using digital media, such as older adults. These individuals potentially need additional personal assistance or monitoring to assure safety during PA (Miller et al., 2014).

Conclusion and Future Directions of JITAI research

The current position paper summarized the knowledge from existing frameworks about JITAIs and synthesized and visualized knowledge into a comprehensive and holistic framework to inform mHealth practitioners about how to implement and report on JITAIs in upcoming mHealth applications. The complexity of designing personalized interventions requires the transdisciplinary collaboration between engineers, computer scientists and behavioural scientists. One of the most important issues is a clear and uniform reporting, which can be informed by the key components of our framework (see Figure 1). Furthermore, reporting should include a clear depiction of the study design (e.g. outcomes, population and duration), methodological approach of the study (e.g. theory used, BCTs and intervention setting) and *Decision Points and Rules* (e.g. precise reporting on algorithms or deep learning mechanisms used) in order to compare different studies and to evaluate best-practice approaches for highest effectiveness.

In conclusion, the framework of the current position paper not only provides a basis for the development of JITAIs but also indicates variables which should be reported by JITAI studies. Future studies should focus on forming consensus on the different parts of the framework to be able to provide a thorough checklist informing researchers and practioners about gold-standards to deploy when initializing JITAI-based mHealth interventions.

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