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Exploring the Design of mHealth Systems for Health Behavior Change using Mobile Biosensors

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Abstract:

A person's health behavior plays a vital role in mitigating their risk of disease and promoting positive health outcomes. In recent years, mHealth systems have emerged to offer novel approaches for encouraging and supporting users in changing their health behavior. Mobile biosensors represent a promising technology in this regard; that is, sensors that collect physiological data (e.g., heart rate, respiration, skin conductance) that individuals wear, carry, or access during their normal daily activities. mHealth system designers have started to use the health information from physiological data to deliver behavior-change interventions. However, little research provides guidance about how one can design mHealth systems to use mobile biosensors for health behavior change. In order to address this research gap, we conducted an exploratory study. Following a hybrid approach that combines deductive and inductive reasoning, we integrated a body of fragmented literature and conducted 30 semi-structured interviews with mHealth stakeholders. From this study, we developed a theoretical framework and six general design guidelines that shed light on the theoretical pathways for how the mHealth interface can facilitate behavior change and provide practical design considerations.

Keywords: Behavior Change, mHealth Systems, Mobile Biosensors.

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1 Introduction

According to the World Health Organization (WHO), health promotion refers to “the process of enabling people to increase control over, and improve, their health” (World Health Organization, 2016). In addition to systemic factors (e.g., availability and pricing of food) and access factors (e.g., ability to pay for food), an individual’s own choices, known as health behavior, plays a vital role in determining their risk of disease and promoting positive health outcomes[1]. Overall, researchers have estimated that the health burden of diseases related to lifestyle behaviors (e.g., cardiovascular disease, diabetes) will amount to US$47 trillion over the next two decades (Bloom et al., 2011), a large portion of which could be prevented by changing people’s health behavior. For instance, researchers have shown that more than 80 percent of cardiovascular events could be prevented if people engaged in health behavior to modify the four main lifestyle risk factors (namely, alcohol overconsumption, inadequate nutrition, physical inactivity, and smoking) (Urrea et al., 2015). Similarly, engaging in a healthier diet and increasing physical activity can substantially reduce the incidence of diabetes (Hamman et al., 2006). However, despite the staggering loss in economic welfare and the associated detrimental impact on people’s quality of life, achieving sustained and lasting change in people’s health behavior remains a societal challenge.

Over the past decade, mobile health systems (or mHealth systems) have emerged as a promising technology to increase people’s control over their health and facilitate health behavior change (O’Reilly & Spruijt-Metz, 2013). Enabled by advances in mobile devices and ubiquitous computing, mHealth systems refer to mobile technology that enhances access to health services (Wowak, Adjerid, Angst, & Guzman, 2016). With respect to health behavior change in particular, mHealth systems offer novel modes for delivering technology-mediated interventions that support users in modifying their behavior for improved health outcomes (Direito, Carraça, Rawstorn, Whittaker, & Maddison, 2017). Thereby, we can define a behavior change intervention (BCI) as a “coordinated [set] of activities designed to change specified behavior patterns” (Michie, van Stralen, & West, 2011, p. 1)[2]. For instance, an education intervention may help a user engage in a healthier diet by providing educational material on the health benefits of increased vegetable consumption through advice in the mHealth interface (Mummah, King, Gardner, & Sutton, 2016). With the wide proliferation and ubiquity of mobile technology in society, mHealth systems enable the delivery of BCIs in a practical and cost-effective way that can reach a large number of individuals and that may be tailored to the individual user (Direito et al., 2017).

The increasing availability of mobile biosensors represents one recent key development for mHealth systems design; that is, sensors that collect physiological data (e.g., heart rate, respiration, skin conductance) that individuals wear, carry, or access during their normal daily activities (Kumar et al., 2013; Urrea et al., 2015). Combined with contextual information (e.g., location and self-report data), the data obtained from mobile biosensors provide valuable insights into a person’s health status and their lifestyle choices (e.g., risk for cardiovascular disease and diabetes) (Ballinger et al., 2018). For instance, mobile heart rate sensors can provide insights into how a person’s self-reported smoking habits affect their resting heart rate, and researchers have linked high resting heart rates to an increased risk of cardiovascular disease (Palatini et al., 2006; Papathanasiou et al., 2013). Similarly, biosensors for measuring heart rate, respiration, and skin conductance provide insights into a person’s (physiological) stress levels even before individuals consciously perceive stress (Riedl, 2013). mHealth system designers have started to use this source of health information to deliver BCIs. For instance, Xiong, He, Ji, and Wu (2013) used mobile biosensors to deliver a training intervention for building individuals’ capability to perceive and control physiological stress responses. By creating a feedback loop between a user’s behavior and the physiological changes resulting from that behavior, the system enables users to train to control their physiology with paced breathing exercises while receiving real-time biofeedback on their heart rate and respiration. However, despite the widely acknowledged potential of mobile biosensors, little research provides guidance for how one can design mHealth systems to use mobile biosensors for health behavior change (Free et al., 2013; Kumar et al., 2013; Payne, Lister, West, & Bernhardt, 2015).

[1] Note that the terms health promotion and health behavior refer to *people* in general rather than *patients*. Hence, promoting a person’s health does not focus only on treating a particular disease. Instead, acknowledging people as the main health resource, health behavior refers to mitigating risk factors and pursuing positive health outcomes (World Health Organization, 1986).

[2] As Michie et al. (2015) describe, an effective BCI commonly builds on one or more specific behavior-change techniques (i.e., observable and replicable components for changing behavior). The authors identified 93 different techniques (e.g., self-monitoring of behavior, information about health consequences, feedback on behavior) that BCIs commonly employ.

In this paper, we address this gap by conducting an exploratory study to inform the design of mHealth systems that use mobile biosensors for facilitating health behavior change. In particular, we follow a hybrid approach that combines deductive and inductive reasoning. First, we integrate a body of fragmented literature (deduction) to develop a theoretical framework (Gregory & Muntermann, 2011). We used this body of (albeit fragmented) literature to derive specific propositions that bring to light the theoretical pathways for how mHealth systems may facilitate health behavior change by using mobile biosensors. In doing so, the framework may support systems development by providing researchers and practitioners with a shared frame of reference that allows them to systematically map out how mHealth interface elements can target individual components of behavior and the types of BCIs that allow them to do so. Second, building on this theoretical groundwork and the stakeholder groups that we identified in the mHealth literature, we conduct a series of exploratory interviews (induction) with representatives from the identified stakeholder groups (health practitioners, health insurance providers, health behavior scientists, IT professionals, designers, policy makers, and users) based on which we developed six general guidelines for designing such systems. The guidelines add to the mHealth knowledge base by providing system designers with a starting point of practical design considerations that consider multiple stakeholders' perspectives. In this vein, we address the following overarching research question:

> **RQ:** How can one design mHealth systems to use mobile biosensors for health behavior change?

This paper proceeds as follows. In Section 2, we overview previous research on designing mHealth systems for behavior change and the challenges that arise in that context. In Section 3, we present the research methodology for the hybrid approach we employed. In Section 4, we present the results of our deductive theorizing and introduce an integrative theoretical framework for mHealth systems in the context of health behavior change. In Section 5, based on thematically analyzing the interviews, we derive six general design guidelines for designing mHealth systems that use mobile biosensors. In Section 6, we discuss our findings, the study's limitations, and opportunities for future research. Finally, in Section 7, we conclude the paper.

2 Related Work and Background

2.1 Related Work on Designing mHealth Systems for Behavior Change

Driven by the ubiquity and increasing capabilities of mobile user devices in recent years (Danaher, Brendryen, Seeley, Tyler, & Woolley, 2015; O'Reilly & Spruijt-Metz, 2013), mHealth systems have become a growing area for IS research and practice. mHealth refers to "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" (World Health Organization, 2011, p. 6). According to recent estimates, the number of mHealth apps on the major online stores related to mHealth exceeds 250,000 (R2G, 2016). The two primary application domains that have emerged for mHealth systems over the past decade include: 1) disease management and 2) health behavior change. First, disease management focuses on patient-centered care (Stewart, 2001); that is, on empowering patients to manage their medical conditions more effectively and more independently (e.g., helping diabetics control their blood sugar) (Kitsiou, Paré, Jaana, & Gerber, 2017). Second, health behavior change focuses on preventing disease by facilitating better health choices; that is, on supporting and encouraging users to engage in health behaviors that promote positive health outcomes (e.g., improved diet, smoking cessation). In this paper, we focus specifically on the latter category.

Scholars have recognized that a mHealth system's design plays an important role in its effectiveness for bringing about behavior change. They have identified several factors for effectively designing such systems. First, scholars have argued that a theoretical framework rooted in the BCI literature should guide the design of mHealth systems for behavior change (Free et al., 2013; Hingle & Patrick, 2016; Oinas-Kukkonen & Harjumaa, 2009). For instance, Hingle and Patrick (2016) argued that a profound understanding of BCIs is critical when making recommendations to users in regards to changing their behavior and that this ideally should be accomplished through the use of an established intervention framework. Similarly, Labrique, Vasudevan, Kochi, Fabricant, and Mehl (2013) argued that the lack of a common framework creates difficulties in identifying, cataloging, and synthesizing evidence for designing mHealth systems. Hence, guiding the design with a theoretical framework also helps one to evaluate such systems. However, as Davey, Davey, and Singh (2014, p. 181) note, at this stage, "most m-health studies are not guided by any conceptual framework, neither the research questions are instigated by existing theories”. Hence, we need research that explores how a theoretical framework that is rooted in the BCI literature can guide mHealth system design for health behavior change.

Second, recent reviews of existing mHealth systems (Samdal, Eide, Barth, Williams, & Meland, 2017) and Web-based eHealth systems (van Genugten, Dusseldorp, Webb, & van Empelen, 2016) have shown that systems more effectively bring about behavior change if their design implements a higher number of behavior-change techniques. However, at this stage, mHealth systems employ a small number of techniques in delivering BCIs (Conroy, Yang, & Maher, 2014; Direito et al. 2017). For instance, in reviewing the 200 most popular mHealth apps (free and paid apps on Apple iTunes and Google Play), Conroy et al. (2014) found that apps for physical activity on average implement only four techniques in delivering BCIs (see also Direito et al. 2017). Similarly, in reviewing systems for alcohol reduction, Crane, Garnett, Brown, West, and Michie (2015) found that the reviewed systems implemented less than four behavior-change techniques on average (Crane, Garnett, Brown, West, & Michie, 2015). Hence, system designers need to consider how they can implement a larger number of techniques through the different BCI pathways. As we describe in the above paragraph, a framework grounded in the BCI literature should guide designers in implementing these techniques (Garnett, Crane, Michie, West, & Brown, 2016; Hingle & Patrick, 2016; Vandelanotte et al., 2016). In particular, guiding the design with an established BCI framework enables system designers to implement a higher number of behavior-change techniques because they can systematically consider a range of different potential pathways for implementing BCIs in their artifact (Michie et al., 2015).

Third, scholars have argued that system designers should consider the potential of mobile biosensors in delivering BCIs. More broadly, the design strategy of using biosensors as built-in information system (IS) functions (vom Brocke, Riedl, & Léger, 2013, p. 3) allows designers to develop “systems that recognize the physiological state of the user and that adapt, based on that information, in real time” (Riedl, Davis, & Hevner, 2014, p. i; see Lux et al., 2018, for a review). In doing so, mobile biosensors can facilitate a feedback loop between users’ health behavior and their physiological state (e.g., biofeedback (Xiong et al. 2013; Uddin et al., 2016) and, thus, just-in-time interventions (Gutierrez, Fast, Ngu, & Gao, 2015)). For instance, Adam, Gimpel, Maedche, and Riedl (2017) conducted a series of interviews to explore how employing biosignals may help designers develop stress-sensitive enterprise systems that support users in managing and reducing stress through interventions at the individual (e.g., biofeedback to increase stress awareness) and organizational levels (e.g., organize break schedules by understanding stress patterns). Based on systematic reviews of academic literature on the effectiveness of mHealth systems, Free et al. (2013) and Schoeppe et al. (2016) concludes that, overall, we have 1) limited evidence for the effectiveness of mHealth systems (with the exception of SMS) and (2) a need to further explore how one can use technologies such as mobile biosensors and video in delivering BCIs[3]. Hence, in the present paper, we specifically focus on the case of mobile biosensors as a promising technology for bringing about behavior change.

Fourth, mHealth stakeholders’ involvement plays a critical role for the design process (Facchinetti, Fernando, & Quoi, 2012; Lobelo et al., 2016; Petersen, Adams, & DeMuro, 2015). For instance, Eckman, Gorski, and Mehta (2016) argued that successful mHealth design requires collaboration between all stakeholders and their input. Several scholars have suggested co-design methods as a potential mechanism for stakeholder collaboration. For instance, Marzano et al. (2015, p. 947) argued that the challenge of mHealth systems design “is a multidisciplinary one and is likely to be best met through a careful process of co-design”. Similarly, Burke et al. (2015) argued that one can address many of the pitfalls in current mHealth approaches through a process of interdisciplinary collaboration that includes end users in all phases. However, despite suggestions for using co-design in mHealth, little research has used co-design in the context of mobile biosensors and health behavior change[4]. In the present paper, we engage with different mHealth stakeholder categories to conduct exploratory interviews in order to develop a set of general guidelines to support system designers in designing mHealth systems for

[3] Reviewing 26 randomized control trials, Free et al. (2013) found that, other than SMS-based interventions (e.g., for smoking cessation), mHealth-based BCIs had limited effects on health outcomes. Specifically, Free et al. (2013 p.3) referred to primary outcomes (i.e., objective measures of health or health service delivery or use) and secondary outcomes (i.e., self-reported outcomes). Similarly, Schoeppe et al. (2016) found limited effectiveness in reviewing 30 studies with a focus on diet and physical activity.

[4] Donetto, Pierri, Tsianakas, and Robert (2015) investigated the application of co-design in the healthcare context but did not discuss mHealth specifically. There have also been several instances of mHealth system design in the mental health context (Bardram et al., 2013; Ben-Zeev et al., 2015; Thieme et al., 2016); however, none of these studies specifically looked at the potential of mobile biosensors.

behavior change. Hence, we do not co-design an actual mHealth system artifact but instead engage with stakeholders to explore design considerations based on multiple perspectives.

2.2 Involvement of Stakeholders and Remote Systems

While scholars have recommended better involving stakeholders in the mHealth design process (e.g., Eckman et al., 2016; Lobelo et al., 2016), to our knowledge, little research defines the necessary mHealth stakeholders and their degree of involvement in this process. Based on reviewing the literature, we overview stakeholders and remote systems and how they interact in the context of mHealth systems and health promotion in Figure 1. Overall, we identified seven different stakeholder groups that may contribute important information to the design: designers (D), health behavior scientists (HBS), health insurance providers (HIP), health practitioners (HP), IT professionals (ITP), policy makers (PM), and users (U) (Facchinetti et al., 2012; Lobelo et al., 2016; Petersen et al., 2015; Vandelanotte et al., 2016). Thereby, the term direct stakeholders refers to stakeholders who participate in designing and using the system, whereas indirect stakeholders refers to stakeholders who participate in designing the system but do not directly use it themselves. For instance, HPs represent direct stakeholders as they could use a mHealth system to monitor users through a remote system, whereas HBSs and PMs have important influencing and supporting roles. Specifically, designers require HBSs' expertise when designing a mHealth system as the latter's input ensures that the system builds on an established BCI framework (Lobelo et al., 2016; Petersen et al., 2015). PMs and HIPs, on the other hand, can provide financial support for mHealth systems and make policy decisions based on the data obtained from them (Facchinetti et al., 2012).

Further, in identifying the different stakeholder categories, we highlight the need to understand how one can integrate other systems into the approach. Specifically, we identify a set of *remote systems* that arise in the mHealth system context. These remote systems are separate from the user device and allow for more complex data analysis and other stakeholders' involvement (e.g., HPs). The first remote system, the data-aggregation and -analysis service, aggregates and analyzes user data to allow for more detailed feedback such as social comparisons between users. The healthcare provider IS provides information relevant to HPs and allows them to send feedback to users. Lastly, the health insurance provider IS provides information to HIPs that can help them become more involved in health promotion. Overall, mHealth requires remote systems if other stakeholders will have any involvement with the system, and the literature has heavily emphasized the importance of involving these stakeholders (Burke et al., 2015; Hingle & Patrick, 2016; Lobelo et al., 2016). In our interviews, we recruited representatives from all seven stakeholder groups that Figure 1 shows.

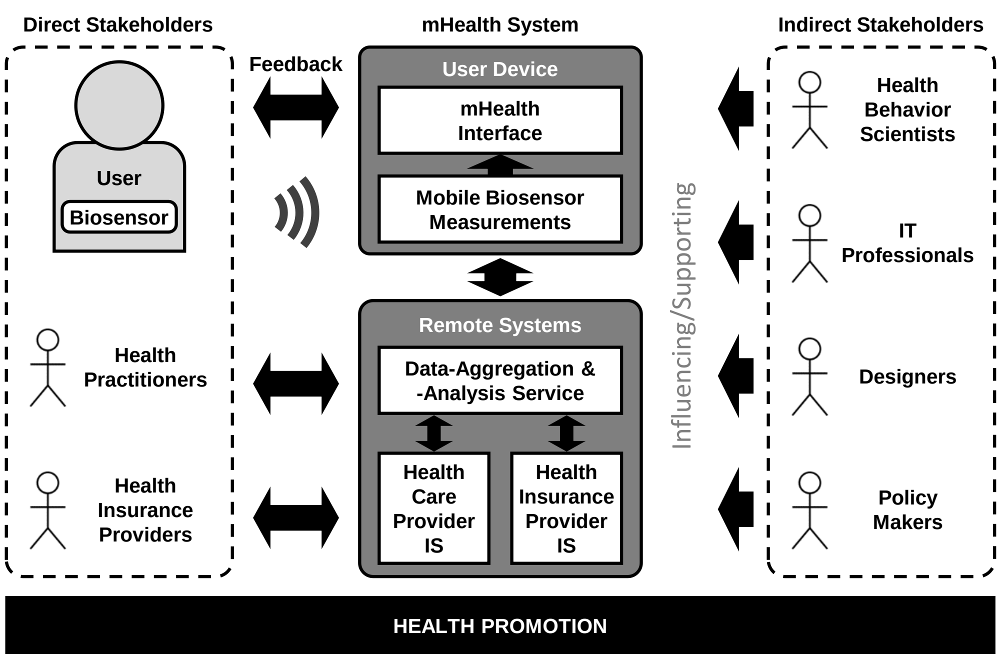

Figure 1. Overview of Stakeholders and Remote Systems

3 Research Methodology

To address our research question, we conducted an exploratory study and followed a hybrid approach that combined deductive and inductive reasoning (Gregory & Muntermann, 2011). By combining deduction and induction, we could build on the advances in the established behavior-change literature to provide a theoretical grounding and focus for our research and could explore a broad range of design considerations based on multiple stakeholder perspectives in the mHealth space. We summarize our research methodology in Figure 2 (see Arnitz, Hütter, & Riedl, 2017, for a similar conceptualization).

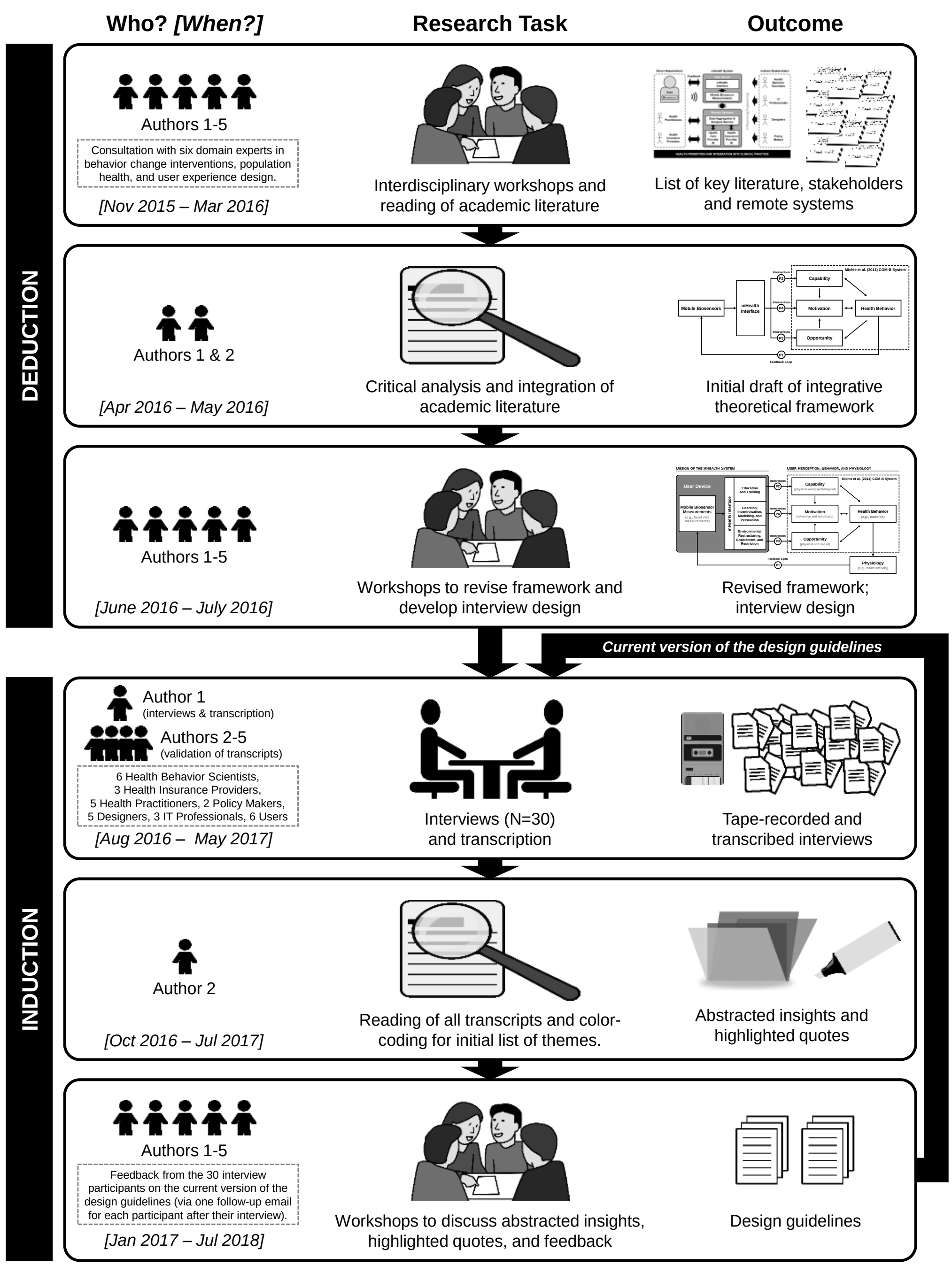

Figure 2. Summary of the Research Methodology

3.1 Deduction: Development of an Integrative Theoretical Framework

Recent research on mHealth systems' efficacy has argued that the design of such systems needs to be appropriately underpinned by a framework grounded in the BCI literature (e.g., Free et al., 2013; Morrissey, Corbett, Walsh, & Molloy, 2016; see also Section 2.1). Thus, in our deductive theorizing, we build on the extant literature to investigate the theoretical pathways for how mHealth systems can use mobile biosensors to facilitate health behavior change and, from this investigation, develop a set of propositions through an integrative theoretical framework as Baumeister and Leary (1997) suggest. In order to address technological and behavioral aspects in designing mHealth systems, in synthesizing the literature, we cover research in the computer science, health, information systems, and psychology disciplines. As Gregory and Muntermann (2011) describe, deductive theorizing in designing information systems builds on critically analyzing and integrating the literature to develop propositions about designing artifacts and the way these artifacts provide utility to their users. Hence, it provides a theoretical underpinning for designing artifacts that has a foundation in the literature.

In the first stage of our deductive theorizing, we used recent reviews on mHealth systems' efficacy (e.g., Direito et al., 2016; Free et al., 2013; Payne et al., 2015), BCIs (e.g., Fogg, 2009; Michie et al., 2011; Weinmann, Schneider, & vom Brocke, 2016), and the integration of biosignals into information systems (e.g., Riedl et al., 2014; vom Brocke et al., 2013) to guide our study. From reading the academic literature, we (with backgrounds in design, information technology, and public health) conducted several interdisciplinary workshops to create a list of key literature, stakeholders, and remote systems for the study's subsequent stages. During these workshops, which lasted between one and two hours each, we engaged in group discussions on existing approaches, findings, and frameworks in the literature that could form the foundation for developing a theoretical framework. In order to actively seek outside expertise, we invited six domain experts to three of these workshops. We selected the domain experts to include a mix of expertise in BCIs, population health, and user experience, and they had between five and 30 years of research experience (avg. 16 years; one industry practitioner, two postdoctoral researchers, three professors). In line with the exploratory nature of this research, we actively encouraged the domain experts to bring in their expertise and suggest key research streams, stakeholders, and remote systems for our study's context. Thereby, we explicitly told them that we sought to work across disciplinary boundaries and integrate a body of fragmented literature. From consulting with these experts, we assembled a list of key literature in the respective areas (i.e., BCI frameworks, biosensor-enabled mHealth systems, co-design, and mHealth stakeholders) and created an overview of stakeholders and remote systems that we needed to investigate further (see Figure 1).

In the second stage of our deductive theorizing, the first and second authors developed an initial draft of the framework by critically analyzing and integrating the academic literature that we identified in the first stage. Based on a set of propositions derived from the literature, the framework conceptualizes the different pathways for how one may use mobile biosensors to facilitate behavior change in a mHealth context. In the third stage, we all then iteratively refined the framework in three subsequent workshops. During these workshops, which lasted between one and two hours each, we discussed the framework's components and how to formulate the propositions. Each author individually prepared for those workshops by working through key literature on BCI interventions and already existing biosensor-enabled mHealth approaches. As such, we could better distinguish the different components of human behavior, separate human physiology from mobile biosensor measurements, and map specific BCI categories with the components of human behavior. We discuss how we formulated the propositions in the theoretical framework in Section 4.

3.2 Induction: Development of Design Guidelines

In our inductive theorizing, we conduct semi-structured interviews to develop a set of general design guidelines for how mHealth systems can use mobile biosensors for behavior change. As Gregory and Muntermann (2011) describe, inductive theorizing in designing information systems enables researchers to integrate domain knowledge by considering multiple viewpoints and perspectives based on real-world experience. We conducted our inductive theorizing to develop general guidelines that can help developers develop mHealth systems that use mobile biosensors for health behavior change.

3.2.1 Interview Design

We used the overview of stakeholders and remote systems (Figure 1) and the results of our deductive theorizing to guide our interview design. We decided to conduct semi-structured interviews because we could use the structure of the theoretical framework that we developed in our deductive theorizing as a shared frame of reference with the interview participants and explore how appropriate design could address the theoretical pathways that the framework captures. We (all five authors) developed the interview design in several workshops, and it comprised three parts (see Appendix A). In the first part, which built on the overview of stakeholders and remote systems, we explored how participants understood mHealth systems in the context of health behavior change and how it affected their own stakeholder domain. In the second part, which concerned the theoretical pathways for how mHealth systems may use mobile biosensors for behavior change, we explored how stakeholders can realize such pathways from their own perspective and whether we missed any theoretical pathways. In the third part, we developed general design guidelines based on the stakeholders' experience and expertise. In order to keep the interviews focused, we decided to refer to mobile heart rate measurements as an example technology of mobile biosensors because heart rate sensors provide important insights into a person's health status (Acharya, Joseph, Kannathal, Lim, & Suri, 2007) and have become increasingly accessible for daily use (e.g., Apple Watch, Samsung Gear). In particular, lifestyle behaviors such as smoking (Papathanasiou et al., 2013) and physical activity (Carter, Banister, & Blaber, 2003) influence heart rate, and research has shown heart rate measurements to be powerful markers for health, specifically as a risk factor for cardiovascular disease, diabetes, and all-cause death (Fox et al., 2007; Palatini & Julius, 1997). For instance, research has linked a high resting heart rate to an increased risk of cardiovascular disease and all-cause death (Fox et al., 2007; Palatini et al., 2006; Palatini & Julius, 1997) and shown a low resting heart rate to protect against cardiovascular disease (Palatini, 2009).

Our early interviews had less structure so we could better grasp the subject matter of the discipline and its role in mHealth. However, as the study progressed, our interview questions became more focused (Easterby-Smith, Thorpe, & Lowe, 2002). All interviews included graphical representations that depicted the integrative theoretical framework that we developed in our deductive research and the overview of stakeholders and remote systems. As the study progressed, we showed the current version of the design guidelines to participants in order for them to evaluate the guidelines and suggest refinements. Further, emphasizing the exploratory nature of our interviews, we explicitly asked participants to identify stakeholders, theoretical pathways, and design aspects that they felt our work lacked. We refined the questions over time as we collected more data. We audio-recorded the interviews so that we could later analyze the responses and use them to iterate on and refine the design guidelines.

3.2.2 Sample

We chose the sample based around the seven stakeholder categories that we identify in Section 2.2 (see Table 1; 30 interviews in total, one interview per participant). We sourced participants by contacting the directors of a medical research institute and of a local health district. We asked them for domain experts as specified in the stakeholder categories. Further, we sourced users from the general population via face-to-face contact and email. None of the participants participated in conducting this research in any capacity. The ethics committee at the University of Newcastle, Australia, approved the study (H-2016-0221), and we obtained informed consent from all participants. Interviews occurred on campus or a location of the participant's choosing. Alternatively, we also conducted interviews via Skype. The interviews lasted for an hour on average; however, they varied in focus and length as the study progressed.

Table 1. Interview Table

Stakeholder category	Number of interviews
Designers (D)	5
Health behavior scientists (HBS)	6
Health insurance providers (HIP)	3
Health practitioners (HP)	5
IT professionals (ITP)	3
Policy makers (PM)	2
Users (U)	6
Total	**30**

3.2.3 Data Analysis and Development of Design Guidelines

The first author transcribed the interviews after which at least one other co-author validated each transcript and sent it to the interview participants to check for potential corrections or omissions. Afterwards, the second author (an experienced scholar in research on human-computer interaction), who did not participate in conducting the interviews, used open and axial coding (Strauss & Corbin, 1990) to analyze the transcripts, which involved carefully reading and color-coding the transcripts in order to identify an initial list of themes for developing design guidelines (91 codes linked to 14 themes). The author identified the themes by critically analyzing the codes assigned to the interview statements against the backdrop of the theoretical framework and by identifying similar design concepts presented across the interviews. Afterwards, in five workshops in which we all participated in, we iteratively refined these 14 themes, which became the basis of the design guidelines. We prepared for the workshops by reading the interview transcripts and carefully checking the second author's analyses. We used the workshops, which lasted between one and two hours each, to arrive at consensus around the themes and design guidelines through a process of selective coding (Strauss & Corbin, 1990). In this process, we examined the initial list of themes and the linkages between them in order to identify general guidelines that best reflected the expressed design considerations. We continued this process until we reached unanimous agreement that the guidelines coherently represented the observations. Finally, we sent each participant one email with the current version of the design guidelines that asked for their feedback. We used any feedback that we received to further refine the design guidelines in the workshops.

4 An Integrative Theoretical Framework

In this section, we develop a framework to capture the theoretical pathways for how mHealth systems can use biosensors to support behavior change. We reviewed existing BCI frameworks to support our framework development, which led to our selecting Michie et al.'s (2011) behavior-change wheel as the main underlying building block. We built on Michie et al.'s (2011) work for several reasons. First, the behavior-change wheel builds on an extensive review of existing BCI frameworks and, hence, comprehensively synthesizes the behavior-change literature. Second, the health-promotion literature has used this BCI framework expansively; as such, stakeholders in health research, which we focus on in our study (e.g., dietary interventions, Robinson et al., 2013; cardiovascular disease risk management, Bonner et al., 2013), recognize it well. Third, due to its simplicity and accessibility, one can apply the framework to a wide range of contexts—an essential consideration to address behavior-change challenges that require cross-disciplinary collaboration such as in our study.

4.1 The Behavior-change Wheel and the COM-B System of Behavior

Michie et al.'s (2011) behavior-change wheel, a BCI framework, allows various users to select and design interventions and policies via analyzing the nature of behavior, the components that one must change to initiate a behavioral change, and the interventions and policies necessary for changing those components. The framework has three layers from outside to inside: 1) policies, 2) interventions, and 3) components of behavior. In this paper, we focus on the latter two layers as developing political interventions lies outside the scope of mHealth system design. The behavior-change wheel catalogs nine different BCI categories (education, persuasion, incentivization, coercion, training, enablement, modeling, environmental restructuring, and restriction) and illustrates how they link to the components that make up behavior. These BCI categories can influence one or more components in the inner most layer of the behavior-change wheel, which Michie et al. (2011) refer to as the COM-B system (see Figure 3).

The COM-B system comprises continually interacting components that generate behavior: capability, opportunity, and motivation (Michie et al., 2011). Capability refers to an "individual's psychological and physical capacity to engage in the activity concerned" (Michie et al., 2011, p. 4). For example, psychological capability involves having the necessary knowledge to achieve a behavioral target, whereas physical capability involves being physically able to achieve a behavioral target. Opportunity refers to "all the factors that lie outside the individual that make the behavior possible or prompt it" (Michie et al., 2011, p. 4). Further, one can subdivide it into physical opportunity (opportunities in the physical environment such as having access to healthy foods) and social opportunity (opportunities in the social environment, such as language and concepts). Finally, motivation refers to "brain processes that energize and direct behavior" (Michie et al., 2011, p. 4). One can break down motivation into reflective motivation (conscious reflective processes, such as planning and evaluation) and automatic motivation (affective processes, such as emotions and impulses)[5]. The single and double-sided arrows in the right part of Figure 3 conceptualize how a change in one component may indirectly influence another and how the generated behavior can re-influence the components in the COM-B system. For instance, an environmental restructuring intervention (e.g., increasing the availability of healthy food) that increases physical opportunity may also indirectly increase motivation due to improving the convenience and access to performing the health behavior (e.g., eating more healthily). Further, achieving this behavior may increase physical capability (e.g., weight loss) and motivation (e.g., self-efficacy), which, in turn, can enable individuals to perform new behaviors.

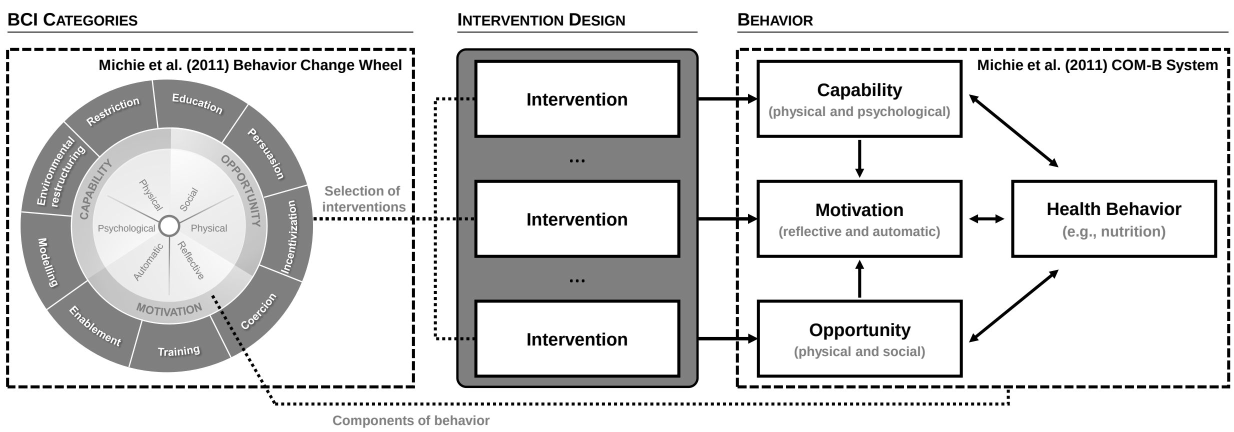

Figure 3. BCI Categories and the COM-B System in the Inner Two Layers of the Behavior-change Wheel

4.2 Framework

In this section, we propose an application of the behavior-change wheel and the COM-B system in the form of an integrative theoretical framework with four propositions (see Figure 4).

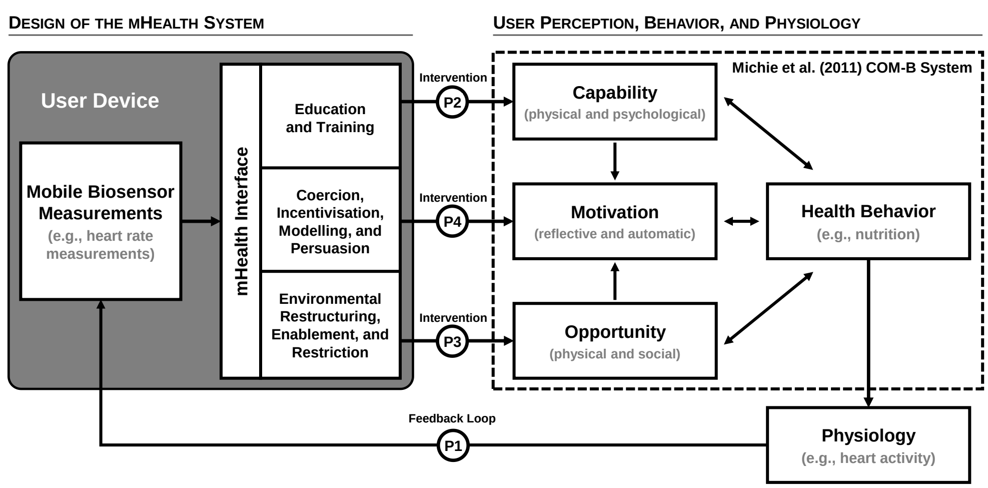

Figure 4. An Integrative Theoretical Framework for Using Mobile Biosensors in mHealth Systems for Health Behavior Change (adapted from Michie et al., 2011)

[5] System designers need to distinguish between reflective and automatic motivation for mHealth since it enables them to systematically explore different pathways for addressing user motivation. As Michie et al. (2014) describe, interventions that target reflective motivation focus on instigating and supporting conscious processes that involve plans and evaluations (e.g., making a plan to stop smoking after reflecting on the health benefits of smoking cessation). By contrast, interventions that target automatic motivation focus on affective responses and the reinforcement of routines and habits (e.g., reminders to reinforce the habit of reduced alcohol consumption). By considering these different pathways, system designers may be more effective in addressing user motivation as they can directly map out and consider how each element of their mHealth interface may target one or even both types of motivation (see also Section 4.6).

On the right-hand side, we conceptualize user perception, behavior, and physiology, which represent the boundary of the user's internal processes. Therefore, note that the perception of the user, which involves their individual circumstances including their physical and social opportunities, influences the effect that an intervention delivered through the mHealth interface (P2, P3, and P4) will have on their COM-B system configuration. Further, we extend the COM-B system in this framework by elaborating on the link between health behavior and its accompanying change in physiology. For example, in the instance of the health behaviors, researchers have shown both physical activity and endurance training to reduce resting heart rate (Carter et al., 2003; Woodward et al., 2014). We argue that mobile biosensors can capture the changes in physiology as a result of enacted health behaviors, which creates a feedback loop between the user's physiology and their perception, a link that users cannot normally perceive (P1).

4.3 Feedback Loop and Mobile Biosensor Measurements (P1)

The feedback loop in our framework encompasses the link between 1) a user's physiology as a result of their health behavior, 2) mobile biosensor measurements that allow the mHealth system to quantify changes in the user's physiology and use it as a system input, and 3) the interventions embedded in the mHealth interface that targets a user's health behavior through capability, opportunity, and motivation. Importantly, a user's health behavior has a direct influence on their physiology regardless of whether the user receives feedback or not. The established literature has documented these links between health behavior and physiology well and shown physiological measurements to reveal early indicators of health conditions (Fox et al., 2007; Palatini et al., 2006; Palatini & Julius, 1997). However, users normally would not be able to discern how their health behavior affects their physiology, and the long-term consequences on their health only become apparent over years or even decades. By using mobile biosensors, mHealth systems have the capacity to close the loop between health behavior, physiology, and user perception; to provide saliency to underlying physiological processes that users cannot usually perceive; and to aid decision making in a motivating and timely way[6]. In other words, while users normally would not be able to see how their health behavior affects their physiology, the mHealth system can make this link apparent and use it in providing interventions (e.g., showing positive physiological consequences of enacted health behavior). These BCIs materialize through the mHealth interface where they can influence capability, opportunity, and/or motivation, which the feedback loop that emerges based on mobile biosensor measurements facilitates.

Research has shown feedback to play an important role for bringing about behavior change. For instance, in control theory (Carvey & Scheier, 1982), which sees behavior as a goal-driven process, feedback facilitates behavior change by revealing the discrepancy between current behavior and a behavioral goal. Revealing the discrepancy between one's current behavior and their behavioral goal creates a feedback loop where one can make corrective adjustments to lower this discrepancy until they attain their behavioral goal or until the discrepancy becomes too great and causes one to disengage from the goal due to a lack of capability, opportunity, or motivation. In the IS context, persuasive systems design also incorporates feedback as a method to change users' attitudes or behaviors (Oinas-Kukkonen & Harjumaa, 2009). Fogg (2009) specifically looks at the link between persuasive design and behavior change through the Fogg behavior model, which posits that, in order for behavior change to occur, a person must have sufficient motivation, have the ability to perform the target behavior, and be timely triggered to perform the behavior. We can see feedback as one form of a trigger in this model. As for Michie et al.'s (2011) COM-B system, note that this framework does not explicitly include feedback as it operates at a higher level of abstraction. However, in subsequent works, Michie et al. (2015) developed a taxonomy of 93 behavior-change techniques for delivering BCIs of which feedback accounts for seven (e.g., biofeedback, feedback on behavior, feedback on outcome(s) of behavior). Therefore, while Michie et al. (2011) do not explicitly mention the feedback concept in their COM-B system, the relationships between the components implies it.

We argue that feedback based on biosensor measurements plays a particularly important role in facilitating behavior change in the mHealth context for several reasons. First, people cannot easily monitor changes in their physiology and, hence, see how changes in their health behavior affect physiological processes because, for the most part, they cannot perceive these processes (Astor, Adam, Jerčić, Schaaff, & Weinhardt, 2013; Riedl et al., 2014). However, with the increasing power, accuracy, and

[6] Miller (1978) states that feedback is important for instrumental learning (also referred to trial-and-error learning or operant conditioning) in that feedback provides information about the successes and/or failures, which provides an opportunity for users to adjust their response. Without feedback, users are "like a blindfolded novice trying to learn to shoot baskets" (p. 291).

accessibility of mobile sensors that collect physiological and contextual data relating to lifestyle behaviors (e.g., location, time of day), one can make these processes salient to the user via feedback—an important factor because changes in physiology (e.g., decreased resting heart rate) usually precede changes that users can visually perceive (e.g., weight loss). By making users aware of their physiological processes that they cannot normally perceive, it makes the relationship between specific behaviors and their resultant physiological changes more salient, which provides users with the opportunity to make more informed decisions. Second, providing feedback can increase self-efficacy or the belief people hold in their ability to influence events that affect their lives (Bandura, 2010). This belief can change based on how capable people perceive themselves to be in their own abilities. By providing feedback on a person's current physiological state, the person will be more psychologically capable due to having access to additional information that they would otherwise not possess. Mobile biosensors can provide information about the connection between behaviors performed and their subsequent effects on physiology. As a result, this access to information may lead to an increase in a person's perceived control over the outcome of their health and, therefore, lead to an increase in self-efficacy and possibly an increase in motivation to engage in related behaviors.

In sum, feedback plays an important role in behavior change as it can provide users with timely information about their physiological processes in relation to lifestyle behaviors that would normally remain imperceptible and, subsequently, increase users' understanding of how their actions lead to a change in their bodily states. Hence, it makes the connection between health behavior and changes in physiological process accessible to the user in a timely manner.

> **P1:** One can use mobile biosensor measurements to facilitate behavior change interventions through the mHealth interface by creating a feedback loop between users' health behavior and their physiology.

However, the feedback loop that we describe here only refers to the general pathway of mobile biosensor measurements as a facilitator for BCIs. Hence, in order to leverage the potential of the established feedback loop for health behavior change, appropriate mHealth interface design that addresses the components of the COM-B system needs to complement mobile biosensor measurements. Building on this feedback loop, we elaborate on the theoretical pathways for how the mHealth interface can address capability (P2), opportunity (P3), and motivation (P4) in subsequent sections.

4.4 The Influence of the mHealth Interface on Capability (P2)

Capability refers to the psychological and physical capacity to engage in an activity. Without the capability to engage in the targeted activities, an individual cannot achieve a change towards health behavior. Michie et al. (2011) identifies two interventions that one can use to increase capability: education and training. In this section, we discuss how mHealth system designers can use the mHealth interface to increase physical and psychological capability through education and training interventions.

Michie et al. (2011) elaborate that one can increase physical capability through training interventions that facilitate physical skill development. Numerous training interventions use activity sensors for improving physical activity (Glynn et al., 2014), muscular fitness, movement skills, and weight-related behaviors (Smith et al., 2014) by providing instructions on how to perform these behaviors through the mHealth interface. Researchers in the mHealth space have also used biofeedback training to develop skills and improve users' physical capability to regulate their own physiological processes (Lux et al., 2018). For instance, Uddin et al. (2016) developed a mobile training app called Beat that uses an electrocardiographic sensor to provide real-time biofeedback of heart rate variability. The application uses this biofeedback to build the user's skill in controlling their breathing rate to reduce stress and blood pressure. Similarly, Dillon, Kelly, Robertson, and Robertson (2016) used biofeedback for training based on mobile apps that use heart rate and skin conductance for stress management. Hence, one may use biosensors to help users learn to regulate their physiological processes to improve their stress-management capabilities.

On the other hand, Michie et al. (2011) explain that one can accomplish an increase in psychological capability through education and training interventions that impart emotional, cognitive, and/or behavioral skills. Common forms of education interventions in mHealth systems include self-monitoring and performance feedback. Glynn et al. (2014) and Smith et al. (2014) employed education interventions by providing users with performance feedback in relation to previously set health behavior goals (step count and calories burned). Similarly, the Beat app that we mention above employs an education intervention in the form of a performance review that occurs at the end of the training intervention. This review provides the user with feedback on their performance and visualizes the impact of the breathing exercises and biofeedback on stress over time—a relationship between health behavior and physiology that users could not normally perceive. One can also increase psychological capability through training interventions, such as through biofeedback based on heart rate or skin conductance for improving users' emotion regulation capabilities (Astor et al., 2013; Peira, Fredrikson, & Pourtois, 2014).

P2: Mobile biosensor-based interventions that focus on education and training increase users' psychological and physical capability to engage in health behaviors.

4.5 The Influence of the mHealth Interface on Opportunity (P3)

Opportunity refers to the physical and social factors outside an individual that prompt behavior or make it possible. Without the opportunity to engage in a particular activity, one cannot change their behavior. The BCIs that Michie et al. (2011) identify to increase opportunity include environmental restructuring, enablement, and restriction. In this section, we discuss how the mHealth interface can use mobile biosensors to facilitate interventions for increasing physical and social opportunity.

The mHealth interface can assist users in changing the physical factors in their environment that prompt behavior or make it possible via environmental restructuring, enablement, and/or restriction interventions (Michie et al., 2011). Environmental restructuring interventions focus on changing users' physical or social context. One way the mHealth interface can increase physical opportunity through environmental restructuring includes just-in-time interventions; that is, interventions that "deliver support at the moment and in the context that the person needs it most and is most likely to be receptive" (Nahum-Shani et al., 2018, p. 446). Researchers have begun to use mobile biosensors to facilitate just-in-time interventions and, thereby, change how users perceive their environment and, as a result, increase their opportunity to engage in health behaviors. For instance, Saleheen et al. (2015) developed a mHealth system that uses respiration biosensors in combination with movement sensors (accelerometers, gyroscopes) and contextual information (location based on GPS) to detect smoking behaviors and trigger just-in-time interventions to stop smoking. Similarly, Gutierrez et al. (2015) developed a mHealth system that detects alcohol intake for just-in-time interventions using heart rate and skin temperature biosensors in combination with movement sensors (accelerometers, gyroscopes) and location sensors (GPS). The mHealth interface can also increase physical opportunity through enablement, which includes interventions that increase means or reduce barriers beyond education or training (Michie et al., 2011). For instance, based on biosensor measurements (e.g., a detected increase in resting heart rate over time), the mHealth interface may provide individualized behavioral support (e.g., advise on a change in routine), which increases the user's means to engage in a targeted health behavior (e.g., decrease sodium intake). Lastly, the mHealth interface can increase physical opportunity through restriction interventions that focus on reducing the opportunity to engage in adverse behaviors. In this sense, one could also view Saleheen et al.'s (2015) and Gutierrez et al.'s (2015) systems as restriction interventions as they focus on reducing the opportunity that individuals have to engage in consuming alcohol or smoking.

By extending the user's social context (e.g., facilitating access to communities), the mHealth interface can also increase social opportunity in their cultural milieu. To do so via environmental restructuring, mHealth system designers can use mobile biosensors to facilitate social support (i.e., practical or emotional help from friends, relatives, or colleagues). For example, Snyder et al. (2015) developed a mobile biosensor-based system that facilitates social support for stress management. The system displays a user's current stress level (using skin conductance measurements) to people around the user, who can then consider the user's stress levels in their interactions with that individual. Further, Curmi, Ferrario, Southern, and Whittle (2013) developed a system that enables the opportunity for social support during physical activity by sharing the heart rates of triathlon participants with members of their individual social networks in real time. Members of the social network can express their social support by pressing a "cheer" button and the triathlon participant will receive a direct feedback about it through their wearable device. Social comparison represents another way to increase social opportunity through environmental restructuring (i.e., comparing a person's own performance with a peer's). For instance, pointing out the percentile rank of users' physiological stress levels (e.g., based on heart rate and skin conductance) compared to their peers (e.g., same age and gender) creates a social opportunity for them to improve their relative ranking (Lyons, Lewis, Mayrsohn, & Rowland, 2014). Further, mHealth system designers may also use such social comparisons for enablement. For instance, an enablement intervention may facilitate behavioral support by enabling users to engage in online discussions with their peers (e.g., users who exhibit a similar diet and resting heart rate) about practical approaches to attain a certain health goal (e.g., their individual best practice for how they include additional servings of vegetables in their diet in order to lower their resting heart rate), which, in turn, increases their means to engage in that behavior. Similarly, one can address social opportunity through restriction interventions, such as by using mobile biosensor measurements to identify individuals or social groups who exhibit risk behaviors with adverse health effects (e.g., unhealthy diet) and to reduce the number of prompts that the user sees about such behaviors.

P3: Mobile biosensor-based interventions that focus on environmental restructuring, enablement, and restriction increase users' physical and social opportunity to engage in health behaviors.

4.6 The Influence of the mHealth Interface on Motivation (P4)

Motivation refers to reflective and automatic processes that energize and direct behavior (Michie et al., 2011). Motivation has central importance to behavior change because, even if users have the capability and the opportunity to carry out targeted activities, they cannot change their health behavior without a sufficient motivation. The BCIs that Michie et al. (2011) identify to increase motivation include coercion, incentivization, modeling, and persuasion.

Reflective motivation focuses on instigating and supporting conscious processes that involve plans and evaluations. BCIs in the behavior-change wheel that one can use to increase reflective motivation include coercion, incentivization, and persuasion. Coercion interventions involve creating an expectation of punishment or cost, while incentivization interventions create an expectation for a reward (Michie et al., 2011). One way the mHealth interface can use coercion or incentivization involves providing the user with information about current and projected health benefits or ramifications based on their current physiological data and behavior (e.g., future self; Rho et al., 2017). In particular, the health information extracted from physiological data allows to project a user's expected level of wellbeing (e.g., low stress levels) and risk of disease (e.g., cardiovascular disease, diabetes). In this sense, the prospect of disease serves as an expected punishment or cost while the prospect of wellbeing and good health serves as an expected reward. By providing this information to the user, the mHealth system can instigate reflective processes of planning and evaluation (e.g., setting goals to reduce stress levels as measured by skin conductance) in order to change behaviors that lead to these health outcomes (e.g., engaging in stress management). For example, Murray, Hardy, Spruijt-Metz, Hekler, and Raij (2013) discuss how an avatar may mirror users' health information based on biosensors (e.g., stress) and support them in devising a plan to change their health behavior. Building on this notion, the commercial Oakwood Medical Avatar 1) uses an avatar that projects users' current and future health by extracting information from biosensors (e.g., blood pressure, muscle activity) and contextual data (e.g., sleep patterns, weight) and, based on this data, 2) supports the user in planning health behaviors such as following a diet, performing physical activity, and ceasing to smoke (Medical Avatar, 2018). On the other hand, persuasion interventions focus on triggering affective responses and stimulate action (Michie et al., 2011). Persuasion interventions resemble coercion and incentivization interventions except that they focus more on how a message is communicated. For instance, one could make future health consequences based on the user's current behavior that come from mobile biosensors (e.g., smoking and drinking habits detected from respiration, heart rate, and skin temperature) (Gutierrez et al., 2015; Saleheen et al., 2015) even more salient via showing images that depict those consequences (e.g., visually showing weight gain from drinking) or via facilitating a discussion with a health professional to devise a plan for action.

Automatic motivation involves processes that include "emotional reactions, desires (wants and needs), impulses, inhibitions, drive states, and reflex responses" (e.g., reminders to reinforce the habit of reduced alcohol consumption) (Michie, Atkins, & West, 2014, p. 63). BCIs that the mHealth system can use to increase automatic motivation include coercion, incentivization, modeling, and persuasion. Coercion interventions can address automatic motivation, such as by providing well-timed reminders with information about the health consequences of risk behaviors (e.g., reminders containing imagery of negative health outcomes). For instance, the system could use biosensors to detect smoking (Saleheen et al., 2015) or alcohol consumption (Gutierrez et al., 2015) and use reminders to reinforce the formation of healthy habits. Conversely, it could use reminders to increase automatic motivation through incentivization. For instance, Martin et al. (2015) used an incentivization intervention in the form of smart texts that provided positive reinforcement messages to users based on their daily activity goal. Similarly, the system could send positive reinforcement messages to users for every day that it did not detect that they smoked or drank alcohol based on biosensors. Systems can also use modeling interventions, defined as "provid[ing] an example for people to aspire to or imitate" (Michie et al., 2011, p. 7), to increase automatic motivation. For instance, using social comparison based on mobile biosensors (e.g., using respiratory sinus arrhythmia measurements (Xiong et al., 2013) to display a paced breathing leaderboard for stress management) can allow a user's friends or people in a similar demographic to become an example to aspire to for the user based on their positive example. Lastly, a system can use persuasion to increase automatic motivation. Similar to reflective motivation, imagery that makes salient the consequences or benefits of behavior (e.g., visually showing the consequences of having a high resting heart rate) can influence automatic motivation by triggering emotional responses to such visual stimuli.

P4: Mobile biosensor-based interventions that focus on coercion, incentivization, modeling, and persuasion increase users' reflective and automatic motivation to engage in health behaviors.

5 Design Guidelines

Based on the thematic analysis, in this section, we derive six general design guidelines for designing mobile biosensor-enabled mHealth systems for health behavior change (see Appendix B for an overview). As we describe in Section 3.2, the interviews referred to mobile heart rate measurements as an example technology of mobile biosensors.

5.1 Guideline 1: Mobile Biosensor Recordings

This guideline refers to how mHealth systems can measure biosensor data to better understand a user's circumstances and to how it collects contextual data to help it do so. The measurements provide the basis for the feedback loop between lifestyle behavior and physiology. We extensively discussed this topic with participants, and they first noted that the measuring device must be physically tuned to the person. HP1 and HP5 explicitly supported this perspective. Participants also discussed other measurement aspects such as duration, frequency, time of day, and position. In regards to duration, HP1 recommended that, for the example technology (i.e., mobile heart rate measurements), "five minutes is fairly acceptable from current guidelines", which concurs with the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology (1996) that recommend that "5 min recordings of a stationary system are preferred unless the nature of the study dictates another design" (p. 364). The advice from the HPs in regards to time of day and position indicated that consistency in these aspects (e.g., measurement start always around 8 am, always sitting position) has more importance than the specific condition itself (e.g., 8 am vs. 3 pm; sitting position vs. standing position). Further, HP5 added that, in addition to these specific, five-minute recordings, the technology would generally need to keep continuous recordings using a rolling time window of the last 48 hours in order to access this data in case the user exhibited a "funny turn"[7]. Generally, users expressed strong support for using biosensor measurements in mHealth due to two main reasons: to focus on improved visibility and to better understand physiological data in the health context.

In order to better understand biosensor measurements, HPs emphasized that the mHealth interface needs to collect contextual data to interpret the physiological data. A major theme that emerged concerned the degree to which the mHealth interface should passively measure physiological and contextual data or whether the user should manually enter it. Types of passive data discussed included steps, contextual location, blood pressure, and pulse. HP2 and HP4 supported using steps as feedback due to it being a discrete and cheap measure that can complement physiological measurements for determining movement (resting vs. moving heart rate). Further, HIP1 identified contextual location from GPS as useful data as it could assist in understanding the circumstances leading up to health events. However, some users (e.g., U6) disliked using contextual location for privacy reasons. Manually entered data that users discussed included corrective factors for physiological data (e.g., age, sex, medical / family history), whether the user used healthcare resources (e.g., hospital visits), and mood. The mHealth interface needs to collect corrective factors to improve the accuracy of physiological measurements. For instance, β-blocker and rate-limiting medications pharmacologically lower heart rate and, hence, impair the usefulness of physiological measurements as a feedback measure (Palatini, 2009). However, HPs

[7] Storing continuous biosensor recordings over a rolling time window of 48 hours allows the user and their health practitioner access to health information in case of exceptional circumstances. For instance, having access during and/or before a user experiences a "funny turn" provides important information to health practitioners to better understand the circumstances of the event (e.g., atrial fibrillation, tachycardia).

emphasized that this issue concerned chronic disease management more rather than prevention. For example, HP2 stated: “resting heart rate is a measure of fitness as long as people are not confounded with rate limiting drugs”. The majority of participants favored using passive collection due to convenience and accuracy. For instance, in regards to manual entry, U4 stated that they would “[try] to overdo it, which would provide inaccurate results”. In sum, to better understand physiological measurements, the mHealth interface should collect a mixture of passive and manually entered contextual data but use passive measurement as the predominant method.

5.2 Guideline 2: Affective Visual Assets

This guideline refers to using affective visual assets to convey the health information extracted from physiological data in an intuitive and meaningful way in order to increase users’ capability and motivation. This guideline addresses the challenge that users do not find physiological data *intuitive* to understand (capability) and *meaningful* to change their behavior (motivation).

Throughout the interviews, we found that users found it difficult to understand the information embedded in physiological data and how it related to their health goals. For instance, HBS1 emphasized that “as someone from the general population, [heart rate] is not something that you know what it means in terms of what’s good and what’s bad”. U2 echoed this sentiment in stating:

> *Most people aren't aware of their health. A lot of people don't go to the doctor unless they've got a health issue, so most people would have no idea what their blood pressure or heart rate is, or what it means.*

Hence, in order to support users’ psychological capability to engage in healthy behaviors, the mHealth interface needs to convey this information in an intuitive way. In the interviews, participants expressed that appropriately designed visual assets could help bridge the gap between biosensor measurements and user understanding by visually representing the relevant physiological measure. Recent examples in the literature support this notion. For example, Tan, Schöning, Luyten, and Coninx (2014) used visual assets that resemble human elements (heart changing size, sweat droplets) to convey a user’s stress levels extracted from mobile heart rate and skin conductance measurements in an intuitive way. Similarly, scholars have used nature-inspired visualizations as analogies to represent a user’s health status. For instance, Al Osman, Dong, and El Saddik (2016) and Feijs, Kierkels, van Schijndel, and van Lieshout (2013) used visual assets representing trees and flowers that change their appearance based on heart rate and respiration measurements. Hence, by reducing the complexity of the underlying physiological data and by building on analogies, visual assets can aid in making these measurements more intuitive to understand for users and, hence, increase their psychological capability to engage in targeted behaviors.

Further, HBSs emphasized that, even if visual assets convey the health information in an intuitive way, it would not motivate users to engage in health behavior change unless this change becomes meaningful to them. For instance, reducing a stress level measure extracted from respiration or skin conductance data may in and by itself not sufficiently motivate individuals to change their behavior. Hence, in order to not only address capability but also motivation, designers should design visual assets in a way that makes it meaningful for the user to change their behavior. In particular, HBSs argued that designers should design visual assets to be affective in the sense that they can create an emotional bond with the user. For instance, HBS3 suggested that using affective visual assets could make interventions more personal as it “might feel like you're actually talking to a person rather than just getting a brochure telling you to not smoke”. During our interviews, three particular types of visual assets emerged for this goal: 1) mirrored-self avatars, 2) persuasive avatars, and 3) embodied agents. The mirrored-self avatar concept that Behm-Morawitz (2013) employed showed that the appearance of an avatar representing a user can influence the real-world behavior of that user[8]. For instance, a mirrored-self avatar could change its appearance (e.g. weight, age, skin) based on the user’s physiological data (e.g., stress level, smoking, and alcohol intake). Hence, by mirroring the user’s health status, a mirrored-self avatar may establish a meaningful and, at the same time, intuitive link between the user’s physiology and their health behavior. HBS1 supported the mirrored-self concept, particularly for increasing self-efficacy, in stating:

[8] An avatar refers to “a perceptible digital representation whose behaviors reflect those executed, typically in real time, by a specific human being” (Bailenson & Blascovich, 2004, p. 64). Yee and Bailenson (2007) show that users that had more physically attractive avatars displayed increased confidence and kept shorter personal distances in virtual interactions compared to users who operated less physically attractive avatars. The authors explained this behavior with the Proteus effect.

> *I think it does tie into the self-efficacy because, when people are doing well, their avatar can reflect that. But I think it's also reinforcing in terms of the capability in the COM-B model because that's one of the issues is people not believing that they can do it or how to do it.*

In contrast, a persuasive avatar represents another person, typically an authority figure (Hanus & Fox, 2015) such as virtual doctors (Fujita, Hakura, & Kurematsu, 2010) and virtual coaches (Buttussi, Chittaro, & Nadalutti, 2006). For example, the mHealth interface could provide feedback on biosensor data (e.g., stress levels based on respiration and skin conductance) through a persuasive avatar representing a HP (increasing trust and credibility when users interpret physiological data; see Guideline 4). While participants generally supported the concept of a persuasive avatar, HBS4 added that one needs to carefully consider the level of persuasiveness considered against the backdrop of the "person's relationship with authority figures". Several users raised similar concerns. Finally, embodied agents emerged as a third type of visual asset in the interviews. For instance, virtual pets represent a type of embodied agent that employ a mix of anthropomorphic and non-human elements and are influenced by user engagement (Kromand, 2007). Similarly, the mHealth interface can use nature-inspired elements such as trees and flowers (e.g., reflecting physiological stress; Al Osman et al., 2016, Feijs et al., 2013) that we discuss above to address motivation via an embodied agent that makes a change in physiology more meaningful. In the interviews, participants saw virtual pets as suitable for younger users since game settings typically feature such pets.

While all participants generally embraced affective visual assets that convey the user's physiological state (particularly in terms of addressing capability), we realized that users themselves need to choose which visual assets the mHealth interface employs in order for it to effectively address motivation. For instance, in the context of avatars and embodied agents, participants expressed a large variance in their preferences. Further, U1 stated that avatars would not work for them at all but that other affective visual assets would with the key that the user could individualize the asset: "if somebody is an enthusiast in a different area, it could be aimed at the things that they are enthusiastic about". Among the assets, the mirrored-self avatar received the most support but also the most criticism. Participants saw the degree of realism as both a strength and a weakness. While users preferred the directness of the feedback on their physiological state from this avatar (e.g., U2 stated: "I think that people sometimes need to be scared into doing something about their health.… I think it certainly would hit home to us more than just reading numbers and things on a screen"), D1, D5, and ITP2 stated that it could be very confronting and eerie if the avatar became too realistic to a human (see Mori's (1970) "uncanny valley" notion); therefore, designers might prefer deliberately pursuing a design with moderate human likeness. In sum, while all participants embraced using affective visual assets to convey the user's physiological state overall, when designing affective visual assets, designers need to adequately identify and reflect the motivational factors of a particular target audience in order to effectively address motivation.

5.3 Guideline 3: Goal-setting Support

This guideline refers to how the mHealth interface can use mobile biosensor measurements to provide users with effective goal-setting support. Goal setting represents an important factor for behavior change as it facilitates: 1) capability by showing users *how* they can achieve their goals, 2) opportunity by showing users *when* they can achieve goals, and 3) motivation by showing feedback on *progress* towards goals and boosting self-efficacy (Michie et al., 2015). From the interviews with HBSs and HPs, we found that mobile biosensor measurements have particular usefulness in providing goal-setting support because they can make visible the short-term changes in physiology in response to healthy and unhealthy behaviors (and, hence, increase the saliency of the pathways between physiology and health behavior) and, thereby, help users better understand their progress towards their health goals. For instance, heart rate and skin temperature biosensors can bring to light short-term physiological changes in response to alcohol intake—something users cannot normally perceive (Gutierrez et al., 2015)—which enables them to set and monitor short-term goals around their drinking behavior. In a different example, Paalasmaa, Waris, Toivonen, Leppäkorpi, and Partinen (2012) developed a system where users could specify and monitor goals for their sleep quality (measured by respiration and heart rate) and link this health information to lifestyle behaviors (e.g., alcohol intake, exercise). As such, using mobile biosensors in goal setting allows the mHealth system to break down a user's health goals (e.g., reduced risk for cardiovascular disease) into small and achievable tasks that it can measure and reinforce with biosensors (e.g., reduced resting heart rate). Taken together, using mobile biosensors for facilitating goal-setting support 1) makes lifestyle behavior change more approachable, 2) allows for more opportunities to reinforce or correct behaviors and, 3) attempts to mitigate the problem wherein long-term consequences of unhealthy lifestyle behaviors only become apparent to the user after years or even decades by shortening the time between when the user performs a behavior and when the user receives feedback.

In the interviews, two user interface concepts emerged recurrently when discussing goal-setting support: gamification and serious games[9]. D1 emphasized the importance of gamification for designing mHealth systems in stating “every app we build will be based around the gamification principle in some capacity”. Combining gamification with mobile biosensors can facilitate goal setting in numerous ways. First, gamification can break down unwieldy long-term health goals (e.g., improving stress management) into incrementally achievable goals (e.g., first stabilizing and then reducing stress levels as measured by skin conductance) and reinforce these goals through reminders, which encourage habitual use and facilitate automatic motivation (e.g., reminders reinforcing paced-breathing when detecting high stress levels). HBS5 stated that “[health goals] have to be achievable [and]…something that you inherently want to achieve”. Second, gamification can mitigate the problem associated with the long-term consequences of unhealthy lifestyle behaviors that only become apparent to the user after years or even decades (e.g., onset of cardiovascular disease and diabetes) by providing short-term incentives based on game-like elements and provide feedback on how changes in behavior affect the user’s physiology (e.g., changes in physiological stress levels). However, the participants broadly agreed that the game-like elements represent only a means to an end and that the mHealth system needs to focus on intrinsic goals. For instance, U5 stated: “goals should be intrinsic motivators—things from within”. Self-comparisons and social comparisons represent important factors in this context. All participants strongly supported self-comparison as it provides feedback that focuses solely on users themselves and visualizes their individual progress. Further, self-comparison can increase self-efficacy as it can demonstrate a user’s individual progress over time (e.g., reduction in smoking and drinking occasions as detected from respiration, heart rate, and skin temperature) (Gutierrez et al., 2015; Saleheen et al., 2015). On the other hand, social comparison allows users to compare their physiological state with other similar users (e.g., leaderboards for managing physiological stress levels). Social comparison can be a motivating factor; however, the sense of competition associated with it may also be detrimental for some users. For instance, U5 stated: “I’m the type of person that believes you should only be assessed based on yourself…. Assessing against others can be a demotivator.”.

Next, participants identified serious games, which refer to “games used for purposes other than mere entertainment” (e.g., learning or training; Wattanasoontorn, Boada, Garcia, & Sbert, 2013, p. 231), as another important concept for goal-setting support based on mobile biosensors. By creating a tailored and engaging virtual environment, serious games can provide users with the opportunity to improve their capabilities in a motivating and controlled way. In the context of mobile biosensors and health behavior change, mHealth systems can use serious games to provide users with an opportunity to increase their capability to engage in targeted health behaviors by directly linking game elements to biosensor recordings. For instance, serious games can use heart rate, respiration, and skin conductance biosensors to facilitate paced breathing exercises for relaxation (Dillon et al., 2016; Xiong et al., 2013). HP1, HP2, and HBS2 supported using serious games. Specifically, HP1 stated: “why I like it is that you can in essence control the environment.… You’re controlling the input…. You’ve got the sensor recording and you've got a known environment and you can put stressors in there.”. In this vein, serious games can use biosensors to adjust the game environment to achieve a particular goal. For instance, Dillon et al. (2016) developed a mHealth serious game for stress reduction that used users’ skin conductance levels to progress the interface from a winter scene to a summer scene. In sum, adjusting serious game elements based on physiological data can support goal setting by facilitating a tailored virtual environment that provides users with new opportunities to engage with health goals and improve their capabilities to engage in targeted health behaviors. Because users cannot usually perceive changes in their physiology, they have limited opportunity for such training.

[9] Gamification, which refers to using “game design elements in non-game contexts” (Deterding, Dixon, Khaled, & Nacke, 2011, p. 10), leverages design and interface elements from entertainment games (e.g., achievements, badges, leaderboards, etc.) that provide additional motivation for behavioral changes typically hard to motivate, such as lifestyle behaviors (Schoech, Boyas, Black, & Elias-Lambert, 2013). However, as with every user interface concept, it became apparent that the actual choice and design of the employed user interface concept strongly needs to consider the target audience as gamification and serious games likely have more or less efficacy for particular groups and depend on how the designer ultimately designs these concepts. For instance, HBS6 and U3 suggested that gamification may be effective with younger users but not as effective with the elderly. Similarly, U4 stated that “a serious game could be more of a fad”.

5.4 Guideline 4: External Support

This guideline refers to facilitating a link between mobile biosensor recordings and external resources, which we refer to as external support. Through discussion with participants, we identified two primary types of external support. The first type involves closing the gap between mHealth systems and external stakeholders, particularly HPs. For instance, HP5 stated that mobile biosensor recordings could help them understand a user's physiological state as these measurements better reflect a user's typical day-to-day experience, and phenomena such as white coat hypertension (i.e., elevated blood pressure in the presence of a HP) do not affect them (Martin & McGrath, 2014). By enabling the link to external stakeholders, mHealth systems can address user capability by facilitating information exchange regarding the user's physiological state between the user and their HPs, a source of data that most users do not intuitively understand and, hence, find difficult to interpret. This notion resembles a design concept by Barakah and Ammad-uddin (2012), who proposed a virtual doctor platform where HPs can remotely provide health advice to users based on their medical history and mobile biosensor data (e.g., blood pressure, heart rate). Such information exchange could be made more intuitive and meaningful for users via using affective visual assets (e.g., a persuasive avatar of a doctor; see Guideline 2). Additionally, this form of external support addresses opportunity because it allows the mHealth systems to detect and the user or their health practitioner to act on characteristic patterns in physiological and contextual data where they could not before (e.g., abnormalities in blood pressure, detection of smoking and drinking occasions from biosensors) (Gutierrez et al., 2015; Saleheen et al., 2015). For instance, HP5 stated that, if they had access to physiological and contextual data from mHealth devices, it would help them "to determine what sort of intervention the [user] needs, if at all.… It may be on the wrist of the [user], but it's not available to me.". Also, involving external stakeholders such as HPs into mHealth systems further integrates mHealth into clinical practice. Specifically, participants expressed that involving external stakeholders in analyzing their biosensor data can motivate them by building trust in mHealth systems and these systems' credibility. For example, U5 stated: "doctors are seen as...the ones that you can trust" and that "linking this quite closely with the health professional would support the [mHealth system] and create credibility".

The second type of external support identified involves using physiological and contextual data to provide the user with contextually relevant information from external resources that address psychological capability through education and by creating awareness of opportunities in the physical environment. Among its many benefits, mHealth can provide the user with just-in-time feedback (e.g., when detecting physiological stress based on skin conductance and respiration biosensors) as individuals can immediately access mHealth devices in everyday situations (Danaher et al., 2015; Nahum-Shani et al., 2018). Designers can leverage this ability to point users to external support material (e.g., video materials for paced breathing) and opportunities in the physical environment (e.g., support hotlines, local meditation and healthy eating classes) to reach users when most relevant. In the interviews, HBSs and users emphasized that links to relevant external support resources can support the information that the mHealth system provides directly (e.g., when the user requires further assistance). For instance, U5, who stated "a lot of people don't know how to access places where resources are", argued that this form of external support may be useful as some people lack knowledge of resources available to them. HBS3 added to this sentiment in stating: "It's a really nice way to connect people up with those kind of services that they might not know exist otherwise". In this sense, a mHealth system might prompt users to contact their HP when their physiological data (e.g., blood pressure, heart rate) exhibit anomalies or provide them with a list of relevant services (e.g., local HPs, healthy food options based on location data) based on their location (GPS).

5.5 Guideline 5: Levels of Data Integration

For this guideline, we elaborate on four levels of data integration that connect mobile biosensor data that mHealth systems collect with external stakeholders. Considering the sensitivity of the health information that such systems can extract from physiological data, designers need to adequately address any potential security and privacy issues when integrating these four levels to ensure that all stakeholders can trust the data and have confidence in its provenance.

The first level (level A: individual feedback) refers to the feedback the user sees through the mHealth interface (e.g., using skin conductance to show changes in stress through a mirrored-self avatar). To facilitate this feedback, most current mHealth systems primarily focus on the data stream between the user and the mHealth device; however, this data stream alone cannot effectively address behavior change and neglects integration into clinical practice. Thus, in order to effectively address the propositions, other data connections need to exist as well. Throughout the interviews, we identified three other levels that designers need to consider.

The second level (level B: data-aggregation and -analysis service) refers to a remote system that analyzes mobile biosensor and contextual data from the mHealth device and sends it back in the form of feedback (e.g., facilitating social comparison of health information extracted from physiological data). For instance, ITP1 stated that the design needs to consider the computational complexity of analyzing and aggregating biosensor data by "just [using] this mobile device to collect data and pass this data to a normal computing system and use the most powerful technology to do the aggregation and analysis". ITP1 further explained that implementing a data-aggregation and -analysis service could allow mHealth systems to perform more intelligently than current mHealth systems as it could allow them to apply more sophisticated machine learning techniques, which they need to suggest targeted interventions that consider a user's individual situation. For example, linking the user device to a data-aggregation and -analysis service has the potential to facilitate statistical methods that not only allow mHealth systems to better personalize interventions but also reduce follow-up time due to the ability to "track changes within the individual that predict outcomes (e.g., heart arrhythmias) rather than waiting for the development of discrete, but rare, events (e.g., heart attacks)" (Nilsen et al., 2012, p. 8). Additionally, as several PMs and HIPs emphasized, aggregated data (e.g., average physiological stress levels, severity of smoking and alcohol overconsumption as detected by biosensors) (Gutierrez et al., 2015; Saleheen et al., 2015) could serve as an important source of information for policy creation and resource allocation (e.g., testing effectiveness of health promotion interventions for particular user groups). For instance, PM1 elaborated that: "if you can actually improve the clarity of their vision as to the effectiveness of interventions, then the policy decision becomes much clearer to [PMs] in terms of where should they be investing public dollars". In sum, the data-aggregation and -analysis service not only allows mHealth systems to provide more effective feedback to users but also provides insights about different user groups that could help policymakers craft health promotion policy and indirectly improve behavior change (e.g., better access to support for smoking cessation and related resources in the environment).

The third level (level C: integration with health practitioner information system) refers to a data link that allows HPs to monitor users' physiology and send feedback back to their mHealth device. Enabling this data link between users and HPs addresses users' 1) capability by facilitating individualized feedback from HPs, which can educate them about their physiological state in relation to their health goals (e.g., what their resting heart rate means; hence increasing psychological capability to engage in health behavior); 2) opportunity by enabling users to detect abnormal measurements and act on them proactively (e.g., by suggesting specific health behaviors based on the analyzed biosensor data); and 3) motivation by better integrating mHealth systems into clinical practice, which increases trust and credibility. Users generally supported the data link to a health practitioner IS. For instance, U2 particularly emphasized the usefulness of the system's remote aspect in stating:

> *It would be amazing and very helpful to doctors to not have to sit there and get half an hour's worth of conversation out of somebody as to how they've been. They can just pretty much download that straight onto their system.*

On the other hand, U3 argued that some users may not be open to involving HPs and disliked the idea of having their data visible to them. HPs strongly supported the data link as it further integrates mHealth into clinical practice, allows for in-context measurements, and allows them to monitor users directly. For instance, HP5 stated:

> *If I had a [person] who had extra heart beats in 24 hours and I'm at a conference in Hong Kong, [mHealth systems] should be linked to the [health practitioner IS] in some way so that it's captured and when I see the patient again…, I can look at it.*

Finally, the fourth level (level D: integration with health insurance provider information system) refers to a data link that gives HIPs access to user data. Regarding HIPs' potential role, HIP1 stated:

> *Health and healthier outcomes isn't just about medical advice, but about lifestyle choices…. We can potentially help people make better decisions about their health through getting information to them sooner, and helping connect people who can help each other out.*

However, HIPs currently have a limited role in preventative health as HP2 stated: "we get no data out of primary care until a person has a declared significant medical condition that's had to result in a hospitalization". Using mobile biosensors has the potential to provide important data for preventative health such as whether the user used healthcare resources, factors that lead up to health events, and risk status. HIPs may use this data to provide individual users with direct incentives (e.g., bonus points, financial support) to motivate them and create new opportunities for health behavior change (e.g., support gym membership, discounts for healthy foods)[10]. HIP1 strongly supported this function in stating: "definitely wearables, and definitely phones, and definitely technology would give us that data". Overall, HIPs' involvement in mHealth systems received a mixed response in the interviews with several participants expressing strong reservations. On the one hand, HPs expressed caution about HIPs' involvement. For example, HP5 said: "Whether users would trust you to transmit that data to the insurance provider is a big issue. They might use it for their own commercial purpose…. I don't know if we are ready to involve them yet.". Conversely, users generally supported HIPs' involvement, particularly when they received rewards to increase their motivation for health behavior change. For example, U4 stated: "I like the idea that you can use the application and be rewarded for that by your insurer". PM1 argued that an important factor for convincing users to provide their physiological data to other mHealth stakeholders is that the user should benefit from providing this data and that this benefit, along with a narrative for why the data is being collected and how it will be used, should be clearly communicated. In sum, level D could motivate users on an individual level through targeted incentives and create new opportunities for them through promoting improved health at the population level. However, particularly against the backdrop of the sensitivity of the health information that one can extract from mobile biosensors, designers need to carefully handle HIPs' involvement to ensure that they predominantly consider users' needs.

5.6 Guideline 6: Stakeholder Involvement

This guideline refers to stakeholders' involvement in all design phases. Despite, and more explicitly due to, the promising potential in using mobile biosensor measurements in mHealth systems, system designers must acknowledge that designing such systems for behavior change represents a challenging task and involves difficulties associated with the long-term consequences of unhealthy lifestyle, imperceptibility of short-term changes in physiology, the way in which users understand physiological data, multiple direct and indirect stakeholders with diverse background and interests, sensitive health information from biosensors, and a complex landscape of remote systems. Addressing these challenges and ensuring that the artifact design adequately reflects the intricacies of increasing individual users' capability, opportunity, and motivation to engage in targeted behaviors requires the involvement of all relevant stakeholders in all design phases (Burke et al., 2015; Lobelo et al., 2016). Participants from all stakeholder categories also consistently emphasized this call for a co-design approach in which stakeholders actively participate from the early design stages through to adoption. As HIP1 stated: this involvement ensures that the "technology seamlessly entwines its way in our lives".

Co-design, also known as participatory design, refers to an approach to "facilitate users, researchers, designers and others…to cooperate creatively, so that they can jointly explore and envision ideas, make and discuss sketches, and tinker with mock-ups or prototypes" (Steen, 2011, p. 52).Critically, co-design involves the "user as a partner" rather than designing for the user as a subject (Sanders & Stappers, 2008, p. 5). Supporting this notion, D1 stated that, "if you don't have key decision makers involved in that initial stage, you're doomed". Further, co-design shifts the focus away from technological aims to an emphasis on collaborative activities in contextual and generative design phases (Sanders & Stappers, 2014). As D1 described, "the development is completely…. It's irrelevant". Thereby, co-design emphasizes *contextual* research activities (e.g., using cultural probes and storytelling; Gaver, Boucher, Pennington, & Walker, 2004; Mitchell, Ross, May, Sims, & Parker, 2015) which, as D2 described, help mHealth system designers "to understand the situation that…the problem exists in, and what other various kind of inputs or context surround that" (e.g., individual motivators for health behavior change and contextual factors that may affect biosensor recordings).

[10] For instance, the Australian health insurer Medibank engaged in a joint incentive scheme with Coles, a major chain of supermarkets. In this scheme, Medibank customers receive additional rewards that can be redeemed in their grocery shopping at Coles if their activity levels (as measured by a wearable fitness device) reach a certain goal and/or if they buy healthy foods (e.g., fresh fruit and vegetables) at Coles (https://flybuys.medibank.com.au). A similar incentive scheme was introduced by the South African health insurance company Discovery, where insurance clients were provided with discounts for healthy food purchases at certain supermarkets (An, Patel, Segal, & Sturm, 2013).

6 Discussion and Conclusion

6.1 General Discussion

While researchers have conducted extensive research on how biosensors can provide insightful information about a person's health and lifestyle behaviors, they have only recently begun to use the information from biosensors in designing mHealth systems to deliver behavior-change interventions (Free et al., 2013). As such, we lack any established guidelines for designing such systems, and scholars have raised the concern that a BCI framework often does not guide mHealth systems for behavior change (Davey et al., 2014; Hingle & Patrick, 2016). Against this backdrop, our study's knowledge contribution constitutes an *improvement* (Gregor & Hevner, 2013) because it extends the knowledge base for a known problem with low solution maturity (i.e., mHealth systems design) and high application domain maturity (i.e., health promotion). In particular, our research draws on the BCI literature's deep understanding of health behavior change and develops prescriptive knowledge for designing biosensor-enabled mHealth systems. In doing so, this research makes two core contributions.

First, we contribute the integrative theoretical framework, which formulates the theoretical pathways for how biosensor-enabled mHealth systems can bring about health behavior change. The framework contributes to the prescriptive knowledge base by 1) providing researchers and practitioners with a shared frame of reference for implementing a feedback loop between the user's physiology and their perception and 2) enabling system designers to systematically map out how the elements of their mHealth interface can target individual components of behavior and the types of interventions through which they can do so. Following a deductive theorizing approach, we ground our propositions in Michie et al.'s (2011) well-established BCI framework, which emphasizes that mHealth systems design needs to simultaneously consider users' capability, opportunity, and motivation. In particular, as we discuss in Section 2, previous research has argued that the design of mHealth systems for health behavior change should be guided by a theoretical framework rooted in the BCI literature and that systems more effectively bring about behavior change if their design implements a higher number of behavior-change techniques (Garnett et al., 2016; Hingle & Patrick, 2016; Vandelanotte et al., 2016). Many existing studies focus primarily on increasing users' psychological capability by providing them with additional information or providing that same information in a more intuitive way (Michie et al., 2011). However, putting the focus only on increasing capability would fail to address motivation, which lifestyle behavior change requires (Vandelanotte et al., 2016). Hence, the framework allows more informed decisions as it enables system designers to consider a range of different potential pathways and BCI categories for facilitating behavior change through the mHealth interface.

Second, we contribute six general guidelines for designing mobile biosensor-based BCIs, which we developed in an inductive theorizing approach based on interviews with key mHealth stakeholders. Constructing a mHealth system involves many design choices with links to various different stakeholders and remote systems. In this sense, the guidelines contribute to the prescriptive knowledge base by providing system designers with practical design considerations that consider multiple stakeholders' perspectives. Hence, the guidelines can serve as groundwork for developing new solution artifacts to deliver technology-mediated interventions that support users in modifying their behavior. Importantly, the guidelines do not apply only to a particular type of biosensor (e.g., heart rate, skin conductance) or lifestyle behavior (e.g., nutrition, physical activity). Hence, while individual studies usually focus on an individual solution artifact and a particular type of intervention (e.g., biofeedback training for stress management; Xiong et al., 2013), our guidelines provide general considerations for a bigger class of problems that system designers can then refine for their individual solution artifact. For instance, while several studies have used avatars to convey the health information extracted from biosensors (e.g., Murray et al., 2013), our study abstracts from the particular type of visual asset and instead emphasizes the need for the asset to be intuitive and meaningful to the user. Hence, instead of directly adopting a solution that worked in a different context or for a different cohort, our guidelines allow system designers to make the actual purpose of their individual design choices explicit and to ensure they focus on this purpose throughout the design process. Figure 5 graphically summarizes the direct connections between the six design guidelines and the theoretical framework, which we discuss next.

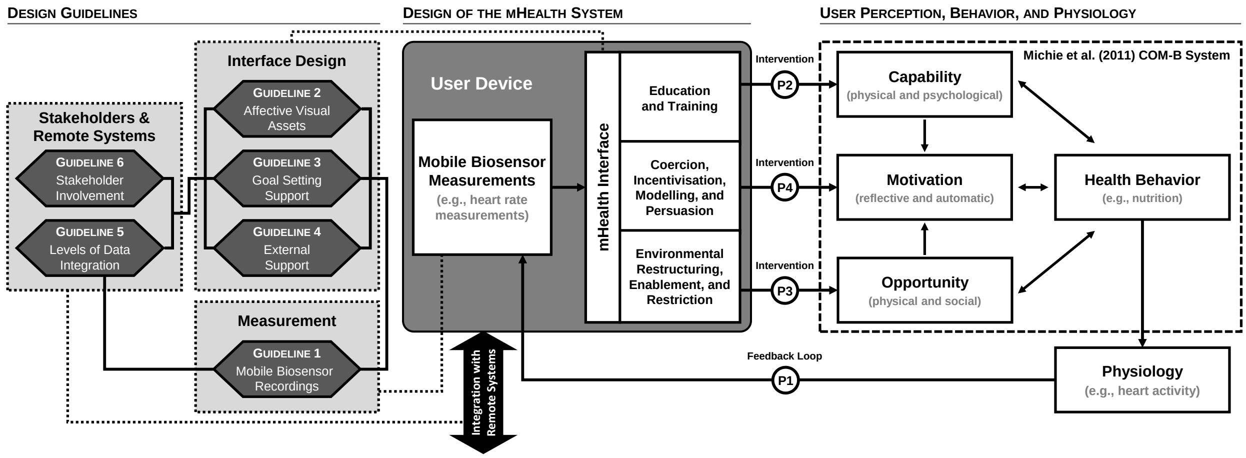

Figure 5. Mapping of the Design Guidelines to the Integrative Theoretical Framework

6.1.1 Measurement

By identifying important considerations in measuring physiological data, Guideline 1 directly relates to creating a feedback loop between users' physiology and their perception (P1). Further, as Figure 5 shows, Guideline 1 also has important links with other design considerations. First, in order to close the feedback loop, the mHealth interface needs to convey the collected physiological data to the user (Guidelines 2 to 4). Second, mHealth systems can use mobile biosensors not only for individual feedback but also to provide external support (Guideline 4) by leveraging data integration with remote systems (Guideline 5). Despite the increased accessibility of sensor technology for consumers, mHealth system designers currently underuse the link to healthcare providers. HP5 emphasized this missing link in stating "all these apps can monitor [heart rate] continuously even now, but it may not be available to your medical practitioner…. We need to close the loop.". Similarly, researchers have called for better integrating mHealth systems into clinical practice (Clifton, Clifton, Pimentel, Watkinson, & Tarassenko, 2013; Lobelo et al., 2016) due to the promise to remotely monitor users and detect medical complications early on (Dobkin & Dorsch, 2011). Hence, by creating a link between a user's physiological measurements and remote systems, external support may assist the feedback loop between a person's health behavior and the resulting physiological changes. This support may help users to better understand how their lifestyle behavior affects their physiology and, subsequently, their health.

6.1.2 Interface Design

The design that the mHealth interface adopts has critical importance for addressing a user's capability, motivation, and opportunity as it mediates the information flow to the user. Building on the foundations of the established feedback loop, Guidelines 2 to 4 directly relate to how designers can implement P2 to P4 in BCIs in the mHealth interface (see Figure 5), which needs to convey the information extracted from mobile biosensors for the user in an intuitive way (P2), create an emotional bond that makes it meaningful for the user to engage in a targeted behavior (P3), and create opportunities for the user to do so (P4). Importantly, these three guidelines relate to one another. For instance, by employing a persuasive avatar, designers can use affective visual assets (Guideline 2) to effectively facilitate external support (Guideline 4). One way of accomplishing this is by using persuasive avatars that receive input from subject matter experts. Further, by leveraging a health practitioner stereotype, persuasive avatars may be able to activate similar responses from users (e.g., increased trust and credibility) through priming mechanisms (i.e., situational cues and social stereotypes that activate concepts and behaviors) (Bargh & Chartrand, 2000)[11]. Similarly, affective visual assets (Guideline 2) can incorporate goal setting (Guideline 3) in an

[11] Overall, participants agreed that persuasive avatars may be particularly beneficial in the elderly cohort since they could connect to healthcare providers and, thus, increase the cohort's trust in and adherence to the feedback. In the disease-management context, for instance, Javor, Ransmayr, Struhal, and Riedl (2016) show that Parkinson's disease patients had higher initial trust in avatar faces than in human faces. Therefore, a persuasive avatar of a health practitioner may elicit more trust in Parkinson's disease patients than a real health practitioner. However, some participants had concerns about using persuasive avatars. For example, U6 stated: "I know a lot of people have issues with authority so it could be a downfall". Therefore, the success of persuasive avatars may depend on how the user perceives authority figures.

engaging and motivating way. For instance, showing a future projection of users' mirrored-self avatar based on their physiology could increase self-efficacy as it provides an incentive for healthy behaviors and an opportunity to change their behavior before their projection becomes real (Rho et al., 2017). Users strongly supported using projection. For instance, U5 stated:

> *I would love something like that [future self] because you actually know what the end results are going to be and you can see if you need to tweak or do something for your end goal. It's good to set those goals and be able to visually see what you're aiming for.*

HBS6 argued that using a mirrored-self avatar for projecting the future self may "slowly build some sort of capability in [users] to make that sort of prediction". However, HBS2 added that projections that directly concern goals should focus on the short term in stating "you don't want to be projecting something in a week because a week is too long, especially if they're anticipating or struggling now, that's far too long". Therefore, designers can incorporate goal setting into affective visual assets in order to better address capability, opportunity, and motivation.

Importantly, goal setting also has important connections with external support (Guideline 4) as the goal-setting process around physiological data involves consultation with external stakeholders (e.g., HPs). To this end, HP3 and HP5 suggested that mHealth should involve a prescription-like process where the user can set goals with a HP and refine these goals over time through routine checkups. By doing so, HP5 argued, mHealth could better address long-term behavior change. Specifically, HP5 stated: "It should be a long-term process. If you're giving somebody blood pressure medication, you're not in it for a short term. You're for the rest of the [person's] life. It needs to be similar.". Further, users brought up several other benefits of involving HPs in the goal-setting process such as increased trust in the feedback and increased compliance with advice. For example, U4 stated in regards to accountability and long-term use:

> *It puts a face behind what the app is, so then they know if someone of that stature, that profession, has taken the time out to be involved in this, then it's something they would consider not only using, but continue using.*

Therefore, given the difficulty of interpreting users' physiological data and the long-term process and implications of health behavior change, the goal-setting process (Guideline 3) should involve external stakeholders (Guideline 4) in order to tailor users' goals and to increase trust their trust in and compliance with advice.

6.1.3 Stakeholders & Remote Systems

By integrating remote systems (Guideline 5), HPs can not only monitor users' physiological and contextual data remotely but also send feedback back to them (e.g., in the event that a user has a "funny turn" and the doctor wants to arrange an appointment with the user). Furthermore, we clearly found that many existing mHealth systems focus heavily on the data link between the *user* and the *user device* (level A) but do not integrate the *user device* with *remote systems* (levels B, C, and D) (Free et al., 2013). For instance, Winters, Oliver, and Langer (2017, p. 119) emphasizes this missing link by stating that a "lack of informed engagement with health-sector stakeholders and key decision-makers on mHealth innovation…[and] a distinct lack of integration with the formal health system" exists. With the design guidelines that we present in this study, we contribute to better understanding the relationship between mHealth systems and remote systems, which can help to bridge the gap between mHealth and clinical practice. Creating this data link between users and other stakeholders and considering the privacy and security issues that this link entails can improve behavior change outcomes by enabling opportunities that would not exist otherwise (e.g., detection of abnormal measurements that a HP can act on) and improving the credibility of mHealth systems by involving HPs, which could motivate usage intentions and the sustainability of mHealth interventions (external support; see Guideline 4). After all, most people see their HP as a partner in their health and trust them (Roy Morgan, 2017). In this vein, through its connections with the other guidelines, Guideline 5 has indirect links to designing the mHealth interface and the mobile biosensor measurements.

Finally, previous research has emphasized that designers need to include stakeholders early in the design process (Burke et al., 2015; Petersen et al., 2015). By involving stakeholders in all phases of the design process, we can see Guideline 6 as facilitating Guidelines 1-5 in designing BCIs. Hence, Guideline 6 has important indirect links with designing the mHealth system. For instance, co-design can help designers create visual assets that users find intuitive in conveying health information from mobile biosensors and meaningful by addressing a particular target cohort's motivational factors (e.g., adapting a self-avatar or a persuasive avatar; see Guideline 2). By involving stakeholders early in the design process, designers can already determine these motivational factors in the contextual phase. For example, as D1 described, by engaging users in co-design workshops, designers can collaboratively explore how meaningful users find a selection of a particular user interface concept according to their individual motivational pathways, which allows the designers to "find out what that selection means to [the user] as opposed to what you subjectively interpret that information as". Similarly, in order to address the problems associated with the long-term consequences of poor lifestyle behavior, co-design can help designers create compelling goal-setting support (e.g., self-comparison and/or social comparison; see Guideline 3). Further, when devising the information streams between the user device and remote systems, co-design can help to ensure that the mHealth system meets agreed-on ethical privacy and data-protection standards when it handles information from biosensor recordings and other data sources (levels of data integration; see Guideline 5). Thereby, designers need to involve not only the user but also other mHealth stakeholders in the design process in order to address the problem in a way that meets the entire mHealth system's needs.

6.2 Limitations

Our study has several limitations. First, we do not design an actual solution artifact but instead explore general considerations for designing biosensor-enabled mHealth systems at a conceptual level. Hence, designing, implementing, and evaluating a specific mHealth system will require designers to consider the individual problem domain and user cohorts' individual characteristics (e.g., differences in motivational factors for different age groups). For instance, Guideline 2 emphasizes that users face difficulty in understanding and interpreting mobile biosensor recordings, which means that mHealth systems require affective visual assets that convey the embedded health information in an intuitive and meaningful way. However, we did not investigate which particular visual assets prove most effective for a particular user cohort (e.g., young adults) and health behavior (e.g., healthy nutrition). Nevertheless, considering multiple stakeholder perspectives, our design guidelines provide system designers with general points to consider when implementing the theoretical pathways for bringing about health behavior change. Further, our framework can provide researchers and practitioners with a shared frame of reference to map their mHealth interface design to and consider which other theoretical pathways are worth pursuing in it. For instance, using the framework to guide the design may enable system designers who focus on implementing a just-in-time intervention to address automatic motivation (e.g., by using mobile biosensors to detect unhealthy behaviors) to complementarily pursue other BCIs (e.g., education, training) to address capability.

Second, while we developed design guidelines that we contextualize to biosensor-enabled mHealth systems for behavior change, the guidelines may at least partially also apply to designing other types of complex end-user information systems. For instance, affective visual assets (Guideline 2) and goal-setting support (Guideline 3) also represent important design considerations for end-user systems in education (mLearning; Garcia-Cabot, De-Marcos, & Garcia-Lopez, 2015). Similarly, external support (Guideline 4) and data integration with remote systems (Guideline 5) have much importance when designing mHealth systems in disease management (e.g., managing diabetes; Kitsiou et al., 2017)[12]. However, and notwithstanding that some or even all of the design guidelines may also apply to other areas, we note that we developed the guidelines in a process of inductive reasoning based on exploratory interviews for the specific context of mobile biosensors and health promotion. In all stages of this process, we made the exploratory nature of this research explicit to interview participants, and we actively encouraged them to raise any further design considerations that they felt we should include. Further, in our study, we elaborate on why and how the developed design guidelines are important for biosensor-enabled mHealth systems for health behavior change (e.g., difficulty to interpret physiological data, imperceptibility of short-term changes in physiology, sensitivity of health information extracted from biosensors).

Nevertheless, we acknowledge that the guidelines may not all apply at all times and that one may need to adjust them based on the requirements of the system in question. Hence, even though we believe that our guidelines constitute a useful starting point for developing biosensor-enabled mHealth systems, we advise against the mandatory or rote use of the design guidelines. Also, evaluating and refining the proposed guidelines to a particular problem domain (e.g., improved nutrition, reduced alcohol intake) and user

[12] In this context, note that designing complex end-user systems in other contexts may additionally also require other design considerations. Notably, when designing mHealth systems for disease management (e.g., managing diabetes), designers need to consider the specific characteristics and treatment requirements of the respective disease. Because disease management falls outside our scope here, we did not consider such factors in our interviews.

cohort (e.g., young or middle-aged adults) will require dedicated design science projects that involve their own data collection to test the theoretical propositions and evaluate the effectiveness of their solution artifact in bringing about behavior change.

6.3 Future Research

Researchers can extend our findings to future research in several areas. To evaluate the design guidelines we present, we suggest that researchers develop a methodological framework for co-design in a mHealth context since, to our knowledge, no such methodological framework that captures the intricacies of mHealth systems, such as the necessity to include clinical trials at different stages in the design process (particularly for integrating the mHealth system as a facilitator for health behavior change into clinical practice), currently exists. From here, researchers could conduct a co-design study that focuses on a specific cohort from which they can create prototype applications to evaluate and refine the design guidelines. On another note, many mHealth studies have only established the efficacy of intervention effects over a short time (Vandelanotte et al., 2016). Therefore, researchers need to conduct further studies to better understand what BCIs and techniques can effectively bring about sustainable behavior change in a mHealth context over the long term (Burke et al., 2015).

6.4 Conclusion

Mobile biosensors hold great potential for developing mHealth systems that support users in mitigating their risk of disease and promoting positive health outcomes through health behavior change. We hope this study serves researchers and practitioners as a reference guide for designing biosensor-enabled mHealth systems by overviewing stakeholder perspectives that mHealth system designers need to consider, conceptualizing the theoretical pathways for how mHealth system designers can address the components of behavior through different BCIs in the mHealth interface, and providing general guidelines for developing such systems.

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Appendix A: Interview Guide

In this appendix, we provide an example interview guide. Each interview comprised three parts, which we summarize here. While we used the questions provided below as a guide for the interviews, we also asked follow-up questions to the participants' responses.

Part 1: General Understanding of mHealth for Health Behavior Change

Questions:

- What is your opinion on the current state of health promotion? Why do you think it is/isn't working? (HBS, HP, P, U, HIP)
- What advantages do you think mHealth systems could have over traditional forms of health promotion? (All)
- What are the biggest challenges for mHealth systems from a [stakeholder's area] perspective? Why do you think this is the case? Is there anything missing in the existing approaches? (All)
- What do you see as the role of [stakeholder's area] in health promotion? (All)
- From an economic and policy perspective, should mHealth systems focus on rehabilitation/recovery or prevention? Are there specific cohorts should be prioritized initially? (P, HP, HIP, HBS)
- What might the shifts in laws and governance look like as a result of mHealth systems? How can we address them? (P)
- How can we better integrate mHealth systems into clinical practice? (HP)

Material:

- Figure: overview of stakeholders and remote systems (see Figure 1)

Part 2: Theoretical Pathways for how mHealth can utilize Mobile Biosensors

Questions:

- How can we ensure that mHealth systems are tailored to the individual circumstances of the user? (e.g., their baseline). What should the beginning of the health behavior change process look like in a mHealth system context? Who should be involved? (All)
- What are some important considerations when attempting to change health behavior? (HBS, HP, U)
- How important is it that you actually believe that you're going to be successful when trying to change your health behavior? (HBS, HP, U)
- What feedback can heart rate give us about someone's health? How could this feedback be represented in a mHealth system to support health behavior change in the context of a user's capability, opportunity, or motivation? (HP, HBS, U)
- How can resting heart rate and heart rate variability be measured? Would you be able to walk me through the process? What are the factors that need to be considered in a mHealth system context? (HP, ITP)
- How could we use mHealth systems to increase a user's capability / opportunity / motivation in the context of health behavior change? (HBS, HP, U)
- Is there any other data that can be collected from mobile biosensors that would be useful for supporting health behavior change? How should this data be measured and how should it be represented in mHealth systems to address user capability, opportunity, or motivation? (All)
- What do you think is the difference psychologically between starting a health behavior change and maintaining a health behavior change? How should these difference approaches be represented in a mHealth system? (HBS, HP, U)
- What do you think is important for bringing about lasting health behavior change in lifestyle? How can this be applied in mHealth systems? (HP, HBS, HIP, P, U)

- Are there any theoretical pathways that we are missing? (All)

Material:

- Figure: Integrative theoretical framework (see Figure 4)

Part 3: Development of General Design Guidelines

Questions:

- What kinds of measurements could be collected that would be useful in a health promotion context? (HP, U, HIP, HBS, ITP, P)
- Is there any other data (e.g. contextual data such as location, or corrective factors such as age and sex) that should be collected to improve accuracy and/or provide deeper insights into physiological measurements? How should these be implemented in mHealth systems? (HP, ITP, HIP, HBS, U, P)
- What are the challenges or limitations of using mobile biosensors such as heart rate in a health promotion context? How can we overcome/adjust for these? (HP, ITP)
- How frequently can/should heart rate be measured? Why? (HP, HIP, HBS, U, ITP)
- What position should the user be in when measuring heart rate? Why? (HP)
- What aspects of design do you think are important for creating an empathic connection with the user? (All)
- How do you think the mHealth interface should look? What things must be there? How should feedback be represented? Why? (All)
- What stakeholders should be involved in the goal-setting process? Why? (All)
- How should the approach/feedback of mHealth system change for long-term goals and short-term goals? (All)
- How do you think mHealth systems could be utilized for supporting the setting and accomplishment of goals? (All)
- What level of involvement do you think health practitioners and health insurers should have in the use of mHealth systems? (All)
- What are the emerging social, privacy, and security issues to arise as a result of mHealth? How can we address these? (All)
- How can the data collected through mHealth systems be used to support policy decision making? What data is this, and what form should it take? (P)
- What are some potential pitfalls and challenges of designing mHealth systems (D)
- Would you be able to walk me through the design process? (D)
- Are there any particular design methods and techniques you think would be particularly useful for designing mHealth systems? (D)
- Who are the stakeholders in mHealth? What role do you think these stakeholders should have in the design and operationalization of mHealth systems? (All)
- Are there any other design considerations that we are missing? (All)

Material:

- Table: Current version of the design guidelines (see Appendix B)

Appendix B: Design Guidelines Overview

Table B1. Design Guidelines for mHealth Systems that Use Mobile Biosensors for Health Behavior Change

Design guideline	Brief description
Guideline 1: employ dedicated mobile biosensor recordings of adequate length in a resting state combined with contextual data to assess users' overall health status over time while also keeping a continuous recording using a rolling time window to retain critical information in case of a "funny turn".	Mobile biosensor recordings enable a feedback loop between users' physiological state and their perception (P1). For instance, these sensors can easily obtain a user's heart rate, which provides critical information on a person's health status. The recording length of five minutes is an inevitable compromise between convenience and completeness/accuracy. Further, the measurement conditions (i.e., body position, frequency, time of day) should remain as consistent as possible. Contextual data include other collected data such as age, location based on GPS, or medication regime. The mHealth system then interprets the biosensor recordings in the context of the user's holistic health environment to provide timely feedback that appears in and considers the user's individual situation. In case of an adverse event or "funny turn", for example, arrhythmia in heart rate, users and their health practitioners may access additional data by collecting it continuously in a rolling time window (e.g., the past 48 hours).
Guideline 2: use affective visual assets to convey users' physiological state r and make the health information embedded in the biosensor recordings from mobile biosensors more intuitive and meaningful to them.	Users find biosensor recordings difficult to understand in relation to their health goals and lifestyle behavior, which impairs their capability and motivation to engage in healthy behaviors. Appropriate visual assets can address capability (P2) by making the health information embedded in biosensor data *intuitive* for users to understand in the context of their health goals. Further, *affective* visual assets that link their appearance to the user's physiological state (e.g., mirrored-self avatars, persuasive avatars, virtual pets that adjust based on biosensor measurements) can address motivation (P4) by creating an emotional bond between the user and the visual asset that makes a change in behavior *meaningful* to them.
Guideline 3: provide effective goal-setting support to help users develop achievable health goals relating to their physiological state, identify actions they can take to achieve those goals, and increase their self-efficacy through the feedback loop enabled by mobile biosensor data.	The consequences of lifestyle behavior often only become salient over a long period of time, while users cannot usually perceive short-term changes in physiology. Mobile biosensors allow users to identify short-term effects of lifestyle behaviors (e.g., changes in physiological stress levels) and, hence, to break down health goals into small and achievable tasks that link to the users' physiology. Through their user interface, mHealth systems can use mobile biosensors to provide goal-setting support that facilitates capability (P2) by showing users *how* they can achieve their goals (e.g., gamified targets for physiology, biosensor-enabled serious games to train capabilities for behavior change), opportunity (P3) by showing users *when* they can achieve goals (e.g., triggering reminders by using biosensors to detect health behaviors), and motivation (P4) by showing feedback on *progress* in users' physiology and boosting self-efficacy (e.g., self-comparison of physiological data over time).
Guideline 4: provide external support to users by allowing health practitioners to review the biosensor recordings, to allow health practitioners to give feedback to the user, and to provide the user with access to contextually relevant resources based on their physiological state.	Assessing a user's health status based on biosensor recordings is a complex task that goes beyond what an individual user device can achieve. Health practitioners need to be involved and to support the user by reviewing the biosensor recordings, making adjustments to the user's targeted activities and health goals, and providing feedback to the user on their physiological state. External support can extend to recommending a visit to a health practitioner or provide access to external sources of information. Integrating external support into the user interface addresses capability (P2) by facilitating information exchange and opportunity (P3) by making individual adjustment to targeted activities and health goals. The involvement of trusted health practitioners can increase user trust and compliance and can help them to monitor users' physiological data to intervene if necessary.

Table B1. Design Guidelines for mHealth Systems that Use Mobile Biosensors for Health Behavior Change

Guideline 5: consider the four levels of data integration in collecting, managing, and using biosensor recordings while ensuring high levels of privacy and security of sensitive health data and enabling effective support for users and the development of policy.	While mHealth systems primarily focus on the data stream between the user and the mHealth device, mHealth systems also need to consider additional data-integration levels to ensure that the mHealth system uses biosensor data in an effective and responsible way. mHealth systems require data streams of biosensor recordings to remote systems to increase users' psychological capability (P2) by facilitating information exchange, for creating opportunities (P3) by including stakeholders in the goal setting and data assessment process, and for increasing motivation (P4) by facilitating social interactions and identifying the motivational factors of the individual user. We identify four additional data-integration levels: the immediate biosensor data gathering for individual feedback (level A), biosensor data aggregation and analysis (level B), and interfaces with information systems of healthcare providers (level C) and health insurance providers (level D).
Guideline 6: ensure effective stakeholder involvement in all design phases to account for the complexities associated with using mobile biosensor measurements for behavior change and to reconcile the diverging backgrounds, interests, and perspectives of all relevant stakeholders.	While mobile biosensor recordings offer important insights into a person's health status, designing systems to use these recordings for behavior change is a challenging task that involves complexities associated with the long-term consequences of unhealthy lifestyle behaviors, multiple direct and indirect stakeholders with diverse backgrounds and interests, and a complex landscape of remote systems. Actively involving stakeholders already in the contextual and conceptual design phases contributes to reconciling different stakeholder perspectives early and ensures that the mHealth artifact adequately reflects the intricacies of increasing individual users' capability (P2; e.g., convey biosensor information in a way that is *intuitive* for the target cohort), opportunity (P3; e.g., ensure seamless integration of biosensor data with the healthcare provider IS), and motivation (P4; target *meaningful* motivational factors for a particular cohort) to engage in targeted behaviors.

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