Towards A Framework for Mobile Behavior Change Research

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ABSTRACT

Behavior change is one of the most important problems faced by people and researchers today. Behavioral researchers have begun adopting smartphones as data-collection tools in psychological and behavioral science because these devices can study people in their everyday life, objectively measure behavior (using mobile sensing), and implement interventions. From a literature review of recent research on mobile behavior change, we identify three design components: mobile sensing, user contexts, and digital nudges. Informed by these components, we designed three example mobile research applications and propose a solution-focused, conceptual framework for deploying behavior change studies using mobile phones. We discuss future directions for research in psychological and behavioral science as these fields embrace mobile technology.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS

Behavior Change, Behavioral Science, Framework, Mobile Sensing, Digital Nudge, Context, Mobile Phone

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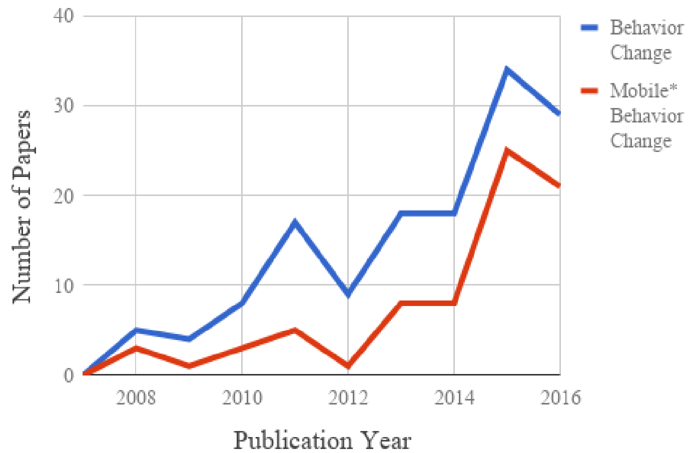

Figure 1: Prominence of Behavior Change Research from 2007-2016 in Selected HCI Proceedings show increasing interests in mobile behavior change

1 INTRODUCTION

Behavior change is considered as one of the major challenges for humans in today's society. Too often, we make choices—what we eat, how we spend our money and time—that undermine our well-being [31]. To improve their lifestyles, people are constantly trying to self-control, change their own behavior and foster good habits; while researchers increasingly study and develop techniques to assist humans in this process.

Traditionally, researchers in psychological, social, and behavioral sciences have collected data about human behaviors in laboratory settings. However, lab studies suffer from external validity because they do not accurately mirror real life settings [2]. In the wild, behavioral researchers often rely on participants' self-reports to measure behavior. But self-reports capture what people say they do but not what they actually do [3], which is a major challenge in behavior change. In addition, self-reports suffer from other limitations including social desirability bias [12] where participants report their responses inaccurately in order to appear favorable to the researcher; and recall bias [8] where participants recollections are inaccurate or incomplete.

Supported by advancements in persuasive technologies that change the way humans interact with digital devices [11], researchers have adopted mobile technology to study and collect data on human behavior [18, 30] across several domains including health, productivity and wellbeing thereby demonstrating the potential of these digital devices. UbiFit Garden [7] encouraged users to engage in more physical activities by using mobile sensing, activity inference, and a glanceable phone background display. StudentLife [32] used passive and automatic sensing data from the phones of 48 students over a 10-week term to assess their mental health (e.g., depression, loneliness), academic performance (e.g. class grades, predict GPA) and behavioral trends (e.g., stress, sleep). However, standalone applications deploy techniques that are not standardized and easily replicable. As such, researchers are turning towards research frameworks for mobile applications.

In recent years, researchers have adopted open source research frameworks to create mobile applications deployed in everyday life. AWARE [10] is an instrumentation framework for researchers

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Table 1: The total number of research papers on mobile* behavior field studies at each publication venue between 2015 and 2017.

Venues	CHI	CSCW	UbiComp	MobileHCI
Mobile Behavior Change	20	3	17	10
Behavior Change	88	31	29	11
Total Papers	1651	486	308	165

*implies that we searched with both "mobile phone" and "smartphone"

and application developers to infer, log, and share mobile phone data. ResearchKit [26], a framework introduced by Apple, allows researchers and developers to create iOS apps for medical research. Using customizable modules of ResearchKit, researchers can easily create visual consent flows, real-time dynamic active tasks, and surveys, which can be shared with the community. ResearchStack [27] was developed as a companion framework to ResearchKit for researchers and developers to deploy medical research apps on Android devices. Although these tools allow the creation of mobile applications that help study human behavior, they were not designed to deploy interventions in mobile phone studies.

In this paper, we propose a conceptual framework for conducting behavior change research studies using mobile phones in the context of people's natural life. We design the framework as a solution-focused research approach [20, 33] that explores behavior change in real-world settings in a standardized, extensible, and replicable way. We identify three dominant components of mobile behavior-change research studies in the literature: *mobile sensing*, *user contexts*, and *digital nudges*. Building on these components, we describe three example mobile applications as a basis for research studies—on user engagement, digital addiction, and differential emotion respectively—that could be conducted using this framework.

2 CONCEPTUAL FRAMEWORK

The conceptual framework is based on a review of published studies described below.

2.1 Review of Studies

As a basis for the development of the conceptual framework we reviewed prior mobile-intervention field studies; in particular, studies published from 2007 (when the first iPhone was created) to 2016. Similar to Hekler et al. [16] who searched ACM Digital Library for "behavior change" in CHI proceedings, we searched for "behavior change", mobile "behavior change", and smartphone "behavior change" in four HCI proceedings—CHI, CSCW, UbiComp, and MobileHCI—to understand how behavior change in HCI has evolved over time. We selected these conferences because they are well-known venues for publishing HCI research that involve mobile phones. Our search yielded 174 papers with over half of these papers from CHI proceedings. Table 1 shows a ratio of behavior change papers across all four conference proceedings. These papers covered multiple domains such as health, productivity, wellbeing and more. Figure 1 shows that as research in behavior change has increased over the years, research in behavior change using mobile

Table 2: Mobile behavior change papers published from 2015 to 2017 with application of mobile sensing, digital nudges, and user contexts. (X) means a design component was present in paper and (-) means it was absent.

Domain	Venue	Year	Sensing	Nudges	Contexts
Health	CHI	2017	X	X	-
Productivity	MobileHCI	2017	X	X	-
Health	UbiComp	2017	-	X	X
Health	UbiComp	2017	-	X	-
Productivity	UbiComp	2017	-	-	-
Productivity	Ubicomp	2017	X	X	X
Productivity	Ubicomp	2017	X	X	X
Wellbeing	Ubicomp	2017	X	X	X
Wellbeing	Ubicomp	2017	X	X	-
Wellbeing	Ubicomp	2017	X	X	-
Health	CHI	2016	-	-	-
Health	CHI	2016	-	X	X
Health	CHI	2016	-	X	-
Health	CHI	2016	-	X	-
Productivity	CHI	2016	X	X	X
Productivity	CHI	2016	-	X	-
Health	CSCW	2016	-	X	-
Health	MobileHCI	2016	X	-	X
Health	UbiComp	2016	X	-	-
Health	CHI	2015	X	X	X
Health	CHI	2015	-	X	-
Productivity	CHI	2015	-	X	-
Health	MobileHCI	2015	X	X	-
Health	MobileHCI	2015	X	X	X
Health	UbiComp	2015	X	-	X
Health	UbiComp	2015	X	X	X

phones has concurrently increased demonstrating that researchers are interested in using mobile phones to drive behavioral interventions.

We focused our search results on mobile "behavior change" and smartphone "behavior change" for three years (2014 - 2017) to capture the most recent trends in the field, which yielded 57 papers. Then, we removed duplicate papers, behavior change papers that are not conducted with mobile phones, papers that used specialized hardware, or did not run field studies. Our final results showed 26 papers—CHI (10), Ubicomp (11), CSCW (1), MobileHCI (4). Selecting major themes from the final set of papers involved considerable decision making. We first developed a rubric key of information that we pulled from each paper and entered it into a document management system including mobile sensors involved (e.g., accelerometer, location, app logging, screen lock and unlock events), mode of intervention delivery (e.g. notification system, SMS, phone calls), and the contingencies of delivery (e.g., after walking, when at a specific location). We did multiple passes to ensure we agreed on the codes, discussing any conflicts along the process. In cases where multiple codes seemed necessary, we accommodated them. We then combined themes into broader categories and arrived at three major design components: *mobile sensing*, *user contexts*, and *digital nudges*. We discuss the rest of this section in light of these design components and show (in Table 2) a detailed summary of each paper and the presence(X) or absence(-) of each component.

Table 3: Areas of opportunity using proposed framework. This is not an exhaustive list but a collection of examples to demonstrate the potential applications of the proposed framework.

Framework Component	Measure of Activity Using Mobile Phone	Technical Approach
Mobile Sensing (detect what a user does)	- Mobility patterns (walking, running, driving) - Daily activities (at work, home, gym, classroom) - Sleep habits - Busyness level	- Accelerometer - Location Services: WiFi scans, GPS - Application logging to monitor apps used - Phone usage patterns (screen lock, unlock events) - Number of phone calls, SMS, and digital calendar
User Contexts (decide when and for whom to intervene)	- Location (intervene at work, home, classroom) - Mood (happy, sad, tired) - Availability (morning, afternoon, evening) - Environment sound (quiet, noisy)	- Location Services: WiFi scans, GPS - Ecological Momentary Assessments (e.g. PAM) - Calendar schedule, sleep time, wakeup time - Microphone audio recordings in environment
Digital Nudges (choose how to intervene)	- Periodic reminder - Draw attention to an event - Provide ongoing realtime feedback - Nudge to engage with specific contents (e.g., planning your day, meditate)	- Push Notification, SMS - Pop-ups, phone vibration, LED display, ringtones - Persistent status bar - Using app intent to launch specific apps (e.g., calendar, todo planner, meditation app)

In the table, "Wellbeing" refers to mental health, while "Health" broadly covers other forms of health.

2.2 Components

We discuss the three identified design components for the proposed framework. To integrate these components into the framework, we adopted a subset of Consolvo's [6] principles for designing behavior change technologies. These include that a persuasive technology should be: *unobtrusive*, *comprehensive*, and *abstract and reflective*. We discuss each of these principles with respect to the framework component that applies it.

2.2.1 Mobile Sensing. Mobile sensing leverages opportunities for measuring user behaviors in diverse contexts given that people's digital devices have formed an integral part of their everyday lives. Mobile sensing involves phone sensors such as accelerometer, location services, screen events, application usage logs, and others. Herari et al. [14] provides a comprehensive overview of mobile phone sensors and the kinds of data that can be collected using these sensors. For example, StudentLife [32] recorded user locations to understand how college students' mobility patterns connected to their mental health. Table 2 shows a summary of the selected papers with several papers (15/26) that use mobile phone sensors including location services, accelerometer, app usages, and more.

We adopted a subset of Consolovo's principles [6] for behavior change technologies when designing the interventions framework to include mobile sensing. These principles explain that a persuasive technology should be unobtrusive by collecting user data without unnecessarily interrupting the user's everyday life. This will be achieved through background tasks on mobile phones that silently collect users' data during behavioral studies without disrupting the normal working operations of their devices.

2.2.2 User Contexts. User context refers to the inferred states of individuals and often include user profile, location, mood and social situation [5]. User context can be directly measured using sensors already embedded in mobile devices or estimated using other sources of small data or digital traces [9]. Measurement of user context is necessary to design personalized and contextual, just-in-time interventions [21]. Our literature survey revealed that 11 out of 26 papers applied user contexts to determine how interventions should be delivered. For example, when a user arrives at a specific location, feedback is sent to the user to engage in a walking activity [22] and when a user uses a distracting app past a daily limit, the user receives an irritating pop-up notification reminding them to exercise self control.

Integrating user contexts into the interventions framework involves the adoption of Consolvo's *comprehensive* principle that states a persuasive technology should account for the range of a user's lifestyle. This will be achieved on the framework by providing functionalities were users can specify their personal contexts.

2.2.3 Digital Nudges. A nudge is an intervention that steers people in a particular direction but does not eliminate their freedom of making the final choice [31]. Nudges were successfully designed and applied to improve decisions about health, wealth and happiness on a policy and individual level. We use the term "digital nudges" to refer to nudges that are provided via digital technology (e.g., mobile phones). Digital nudges can provide information, reminders, and planning prompts to the users in the form of status-bar messages, pop-ups, phone vibration, and phone LED display. Our literature survey revealed extensive use of digital nudges in intervention applications as 21 out of 26 papers applied a form of feedback to prompt users to take an action (see Table 2).

We apply Consolvo's *abstract and reflective* principle for persuasive technologies [6]. This principle states that abstracted data should be used in place of raw data so users can reflect about their behaviors. This will be achieved on the framework through digital nudges that contain clear summarized feedback to users.

2.3 Prototype

We implemented an initial prototype of the proposed framework to support the three critical components described in the previous section (mobile sensing, user context, and digital nudges.) Herari et al. [14] provides details on designing and deploying mobile applications that collect behavioral data in field studies and we applied similar techniques in the design of our prototype. In Table 3, we map each framework component to specific technical approaches for measuring user behaviors and applying interventions. The prototype[1] includes a web interface for researchers, mobile applications for participants, and a backend server, and targets the three example use cases discussed in the next section.

In the future we will integrate existing frameworks (AWARE, ResearchKit and ResearchStack) and connect to third-party services (RescueTime, WakaTime). We will further address broader challenges such as managing diverse mobile platforms, protecting user privacy, and securing data.

3 FRAMEWORK USE CASES

We describe three example research studies that demonstrate the potential of using a framework with standardized and replicable components. Although we present only three example use cases, the framework will support a wide array of research studies.

3.1 Study One: User Engagement

User engagement is an important part of mobile behavioral research in general and mHealth interventions in particular [23, 28]. This example study focuses on the engagement levels of college students using meditation to manage their stress level. Research has shown that college students face different forms of stress throughout their academic experience [17] and meditation is one effective way to reduce stress [19]. A research study could combine *digital nudges* in the form of daily reminders, with *user contexts* in the form of user-configured time-based reminder windows, to measure user engagement.

Using the proposed framework, a researcher could create a new research study that configures a daily reminder message that nudges the user to engage in meditation using Headspace [15], a meditation app. This reminder could be configured to happen within a three hour window selected by the participant at the beginning of the study. Figure 2 shows an example notification that a user receives at the time of the reminder. When the notification is clicked, the Headspace app (installed on the participants' phones during onboarding) would automatically open up for the user to engage in a meditation session. On the other hand, if the user dismisses the prompt to engage in meditation, this event would be recorded.

At the end of the study, the researcher would use a researcher dashboard to access participant data. Although Headspace is specifically used in this study, engagement with any other mobile application can be substituted, the reminder window can be changed and the notification message updated, as appropriate. For example, a researcher could investigate the effects of nudges on daily planning habits by designing a study where a user receives a daily morning reminder to plan each day. Whenever the user clicks on the daily reminder it will automatically open a planner app (such as Google Calendar, Google Keep, or Todoist). The ease of creating engagement studies using this framework opens up more opportunities for behavioral researchers to better understand users' behaviors in natural life.

[1]This is work in progress and project updates can be found at https://slm.smaldata.io.

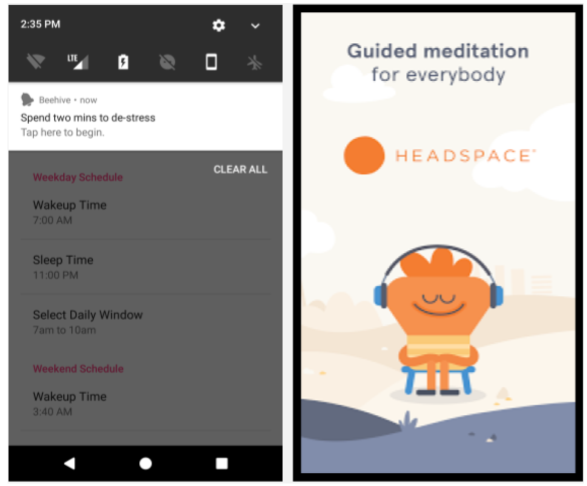

Figure 2: User engagement shows two applications. On the left, the user receives a reminder that nudges the user to engage in meditation; on the right, clicking on the notification opens Headspace^{TM}, a meditation application.

3.2 Study Two: Digital Overload

Although mobile devices provide the opportunity to be assist people in nearly every context and at every moment, research has shown that technology burdens people with the pressure of continual availability [1]. This study example explores reducing Facebook overuse on participants' mobile phones by using pop-up messages. Using the framework, a researcher could monitor participants' social media usage and specify a daily time limit for Facebook (e.g., one hour per day), after which a continuous pop-up message would appear (see Figure 3). This study combines all framework components: *mobile sensing* in the form of app logging, *user contexts* in the form of an action whenever Facebook is overused, and *digital nudges* in the form of pop-up messages and realtime feedback of usage habits.

At the end of the experiment, a researcher could access a log of all mobile applications used during the duration of the experiment. Alternatively, a researcher could easily configure select components of such a study, for example: activate only *mobile sensing* by monitoring app usage logging in the background without administering any pop-up interventions; update *user context* by changing the target application that should receive a pop-up if overused (example, change from Facebook to Gmail); or change the mode of *digital nudge* from showing pop-up messages to vibrating a user's devices. These configurable settings demonstrate the opportunity to study the effects of different interventions on reducing digital overload.

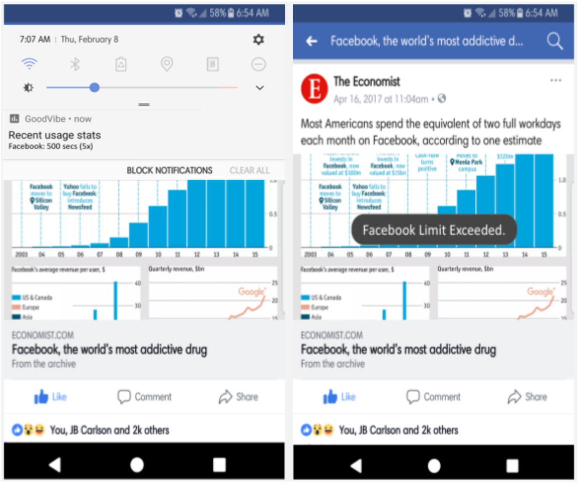

Figure 3: Digital Overload shows two different types of interventions. On the left, one group of users can swipe down the status bar to see realtime feedback of daily Facebook usage (500 seconds in the current day and opened five times); while on the right, another group of users receive a pop-up notification intervention when Facebook daily limit has been surpassed.

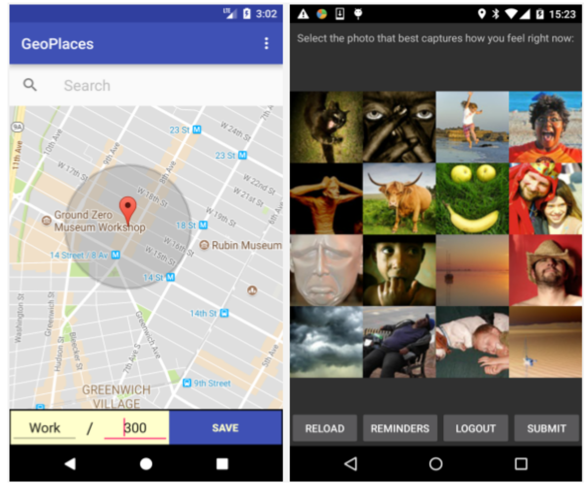

Figure 4: Differential Emotions shows two different applications. On the left is an application for location-based reminder where the user specifies a specific location to receive a reminder—in this case, "work"; while on the right is a validated app, PAM [24], for recording mood. When the user enters "work area", a reminder notification is triggered for the user to record their current mood. When the reminder is clicked, PAM survey opens for the user to select a response.

3.3 Study Three: Differential Emotions

Research has shown that people elicit emotions based on situational contexts and these emotions are accompanied by characteristic patterns [29]. This example study explores how participants' location and time affects their emotions. Using the framework, a researcher could design a study that monitors users' location traces and trigger a survey based on a specific location. This study combines *mobile sensing* in form of location services, *user contexts* in form of location-based reminders, and *digital nudges* in form of timely push notifications that encourage the user to perform an action.

In this study, a user could declare specific locations where they would like to monitor how they feel before and after entering these areas. For example, a user can define "Work" address with a 300 meters radius such that entering that area would trigger a notification asking "How do you feel?". Upon clicking on the notification, a mobile app, Photographic Affect Meter (PAM), would open for the user to log their emotion. Figure 4 shows an example screen of a location app and PAM. PAM [24] has been validated for measuring affect by asking a user to select from a wide variety of photos the one that best captures their current state. At the end of the study, a researcher could make inferences by using participants' responses with their corresponding location labels (e.g. "Work").

4 DISCUSSION

There are several behavioral research platforms for conducting online experiments such as Amazon Mechanical Turk [4], PsiTurk[13], LabIntheWild[25] and others. However, these systems are not designed for conducting mobile field studies. Software frameworks such as AWARE [10] for mobile phones, Research Stack [27] for Android phones, and Research Kit [26] for iPhones can be used for data collection in mobile field studies but they were not designed for conducting behavior-change studies with mobile phones.

Our proposed behavioral research framework targets both data collection and realtime intervention by serving as a layer on top of existing tools. This presents three unique advantages: (1) behavioral researchers can use this framework, in its default state, to systematically deploy and iterate on mobile field studies without requiring technical expertise; (2) we can leverage desirable functionalities of existing frameworks such as AWARE [10], ResearchKit [26], and ResearchStack [27]; (3) researchers and developers can extend the framework as open-source software and build customizable solutions tailored to their own needs.

We designed the proposed framework to be solution-focused [33] by *"prioritizing the development of a solution to a practical problem over the production of generalizable efficacy knowledge that might be correct in abstract but does not represent or translate to any specific real-world setting"* [20]. To inform the design, we analyzed recent mobile field studies in four well-known HCI proceedings (CHI, CSCW, UbiComp and MobileHCI) to characterize the functionalities of mobile applications that were deployed. From our analysis of the selected applications, we identified three dominant components: *mobile sensing*, *user contexts*, and *digital nudges*.

Although these components were based on three years of HCI research on behavior change using mobile phones, they may also reflect the characteristics of behavior change studies beyond three years as well as outside HCI. However, investigating this is outside the scope of this paper. A number of the reviewed papers combined different design components e.g. digital nudges and contexts to achieve just-in-time interventions [21], sensing and nudges, and a few times all three components. Building on these dominant components, we described three example research studies that demonstrate the potential of the proposed framework and the opportunities that lie ahead for researchers interested in conducting behavior-change research studies using mobile phones. Our hope is to contribute to the standardization, replicability and shareability of behavioral research studies using mobile phones.

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