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Feedback Messages During Goal Pursuit: The Dynamic Impact on mHealth Use

Completed Research Paper

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Abstract

To improve mobile health application (mHealth) use, developers often send push notifications to users. Messages that utilize dynamic user data can adapt to users' changing behavior and have the potential to further improve mHealth use and behavior change by delivering the right support at the right time. However, existing behavior change theories are either static in nature or lack temporal specificity. We consider dynamic feedback loops proposed by Social Cognitive Theory to understand how goal and social feedback messages dynamically impact mHealth use during goal pursuit. Using a micro-randomized trial design (n=61) and a custom-developed mHealth application, our findings suggest that the impact of goal and social feedback messages on mHealth use varies based on if users are in the beginning, middle, or end stage of goal pursuit. Moreover, use of specific mHealth features subsequently impacts physical activity behavior. Theoretical reasons for these findings and future research opportunities are discussed.

Keywords: mHealth; behavior change; micro-randomized trial; Social Cognitive Theory; feedback; messages; physical activity

Introduction

Mobile information technologies that monitor the health of individuals, such as smartwatches and smartphones, are becoming increasingly prevalent. These technologies provide the basis for mobile health applications (mHealth) on smartphones (e.g., Strava and Runkeeper). These Information Systems (IS) offer vast opportunities for improving individual and public health. For example, considering rising obesity rates (Ward et al. 2019) and their impact on global mortality (WHO 2020), mHealth has the capability to engage users in physical activity behavior and prevent obesity. However, research on the impact of mHealth on changing users' behavior remains inconsistent (Fallon et al. 2019).

The inconsistent findings are often attributed to decreasing user engagement with mHealth over time (Hardeman et al. 2019). Many app developers utilize push notifications in order to increase use of and engagement with mHealth (Bidargaddi et al. 2018; Spohrer et al. 2021). To improve the impact of push notifications on mHealth use, mHealth can leverage dynamic user data. For example, asynchronous data that is collected by the technology (e.g., minutes of physical activity) can be used to adapt the timing and content of notifications to an individual's changing physical activity behavior over time. On-demand messages that utilize dynamic user data to deliver support when the user needs it most are referred to as just-in-time adaptive interventions (JITAIs). JITAIs can improve the effectiveness of push notifications by adapting the message content and timing of delivery in order to send users the right support at the right time (Nahum-Shani et al. 2015). However, mHealth app developers often have little guidance regarding what content messages should contain, when they should be sent to users, and if this actually impacts mHealth use and behavior change (Hardeman et al. 2019).

Prior work on developing JITAIs suggests that a major challenge lies in existing behavior change theories, which are either static in nature or lack temporal specificity (Nahum-Shani et al. 2015; Riley et al. 2011). Accordingly, there is little theoretical knowledge about how to leverage dynamic user data to inform the content and timing of messages. We rely on Social Cognitive Theory (SCT) (Bandura 1991), which is one of the few behavior change theories that considers behavior change as dynamic and not static (Riley et al. 2016). SCT considers self-regulation of behavior as a dynamic feedback loop that is impacted in response to changing social, personal, and environmental states (Bandura 1991). Within the feedback loop, individuals set goals, monitor behavior, and change behavior in order to achieve their goals (Bandura 1991). During goal pursuit, feedback (i.e., goal feedback or social feedback) can further enhance motivation to continue to pursue goals (Bandura 1991). However, while SCT provides strong theoretical reasons for a dynamic perspective of behavior, it provides little guidance on the time lagged effects. Accordingly, from an SCT perspective, it is unclear if the effects of goal and social feedback are constant (i.e., remain stable during goal pursuit) or variable (i.e., fluctuate during goal pursuit).

In this study, we examine the self-regulation feedback loops proposed by SCT and the effectiveness of feedback messages on mHealth use during goal pursuit. We focus on a user's goal pursuit of achieving a certain amount of physical activity minutes per week and the stages of goal pursuit that indicate how close the user is to achieving that goal (beginning, middle, and end). We aim to determine how the user's stage of goal pursuit can differentially impact the effectiveness of messages with content regarding (1) goal feedback and (2) social feedback. We focus on the impact on both immediate mHealth use and subsequent behavior change. The paper will answer the following research questions:

RQ1: How do goal feedback messages dynamically impact mHealth use at different stages of goal pursuit (beginning, middle, end)?

RQ2: How do social feedback messages dynamically impact mHealth use at different stages of goal pursuit (beginning, middle, end)?

RQ3: How does mHealth use subsequently impact behavior change?

In order to answer our research questions, we deploy a micro-randomized trial (MRT) (Klasnja et al. 2015) using an mHealth app that we developed. Within our MRT, participants are randomized to receive goal feedback and social feedback messages at different stages of goal pursuit. 61 participants from a university in Europe participated in a four-week field study. Objective trace data on use is employed to understand the immediate impact of messages on mHealth use and the subsequent impact on behavior change.

Our findings contribute to IS literature in three key ways. First, we consider the dynamic effects of feedback messages and how the relationship varies over time. The findings contribute to mHealth research by considering dynamic feedback loops of behavior change and to SCT by identifying temporal specificity within the feedback loops (Nahum-Shani et al. 2015; Riley et al. 2011). Second, we conceptualize mHealth use as dynamic instead of employing superficial or binary use concepts. This contributes to research on IS use and provides theoretical grounding for dynamic use concepts (Burton-Jones et al. 2017). Third, prior mHealth research employs study designs that do not allow researchers to understand dynamic feedback loops of behavior change and the immediate impact on mHealth use. We contribute to IS research by employing an MRT and illustrating how this study design can leverage trace data to understand user interactions and treatment effects in a natural setting (Karahanna et al. 2018).

Theoretical Background

In developing our theoretical framework, we draw on three research areas. First, we present a review of mHealth literature that follows an SCT perspective and identify research limitations. Second, we provide an overview of SCT, which outlines the merits of SCT in explaining behavior change and its main tenets. Third, we turn to goal pursuit literature to better understand the psychological processes that occur at different stages of goal pursuit and the time lagged effects of goal and social feedback.

mHealth Use and Behavior Change

We reviewed mHealth research using *EBSCOHost*, *Web of Science*, *JSTOR,* and *ScienceDirect* databases. Included studies employed an mHealth app, assessed objective physical activity behavior for health promotion as a primary outcome, and used an SCT perspective. Studies that focus on mHealth for disease management or clinical populations were excluded because it is expected that these populations differ in their motivations to change behavior and the design of mHealth also differs (Noorbergen et al. 2021). The selected literature focuses on SCT because it is the most widely applied theoretical perspective in mHealth research (Jiang and Cameron 2020; Schmidt-Kraepelin et al. 2020) and is one of the few behavior change theories that considers dynamic feedback loops of behavior change (Riley et al. 2016). The search strategy combined the terms physical activity, mHealth, and SCT (and synonyms) using Boolean operators. The research was analyzed for the application of SCT, the consideration of dynamic feedback loops, the study design used, the evaluation of mHealth use, and the impact of mHealth on physical activity. The review builds upon the premise that IS are used to achieve goals and effective use of IS can increase outcomes of use (Burton-Jones and Grange 2013). An overview of the research is presented in Table 1.

		King et al. (2013)	Al Ayubi et al. (2014)	Rabbi et al. (2015)	Fjeldsoe et al. (2015)	King et al. (2016)	Choi et al. (2016)	Voth et al. (2016)	Zhou et al. (2016)	Fanning et al. (2017)	Ashton et al. (2017)	Torquati et al. (2018)	Korinek et al. (2018)	Liu & Willoughby (2018)	Gremaud et al. (2018)	Arrogi et al. (2019)	Wong et al. (2020)	Romeo et al. (2021)
SCT	Features	x	x	x	x	x	x	x		x	x	x	x		x	x	x	
	Tests SCT						x	x	x	x				x				x
Dynamic Self-reg.	Yes												x					
	No	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x
Study Design	RCT/ RT	x		x	x	x	x	x		x	x			x	x	x		x
	Observational		x						x			x					x	
	Other												x					
mHealth Use Concept†	Binary Use						x	x			x				x	x	x	x
	Extent of Use		x		x				x	x	x	x	x					
	Feature Use		x			x		x		x		x		x				
	Not assessed	x		x														
Impact on PA	Yes		x	x	x			x	x	x			x	x	x	x	x	
	Inconclusive	x				x	x				x	x						x

Table 1. Overview of Literature Review

SCT=Social Cognitive Theory; Self-reg.= self-regulation; RCT=randomized controlled trial; RT=randomized trial; PA=physical activity; †Based on Burton-Jones & Straub (2006) and Fallon et al. (2019), Binary use=mHealth vs. no mHealth; Extent of Use=time spent in app or app logins; Feature Use=number and type of features used.

Three overarching research limitations were identified in the reviewed literature: (1) dynamic feedback loops proposed by SCT are often ignored; (2) current experimental designs are not adequate for assessing time-variant and within-person dynamic processes during mHealth use, and (3) overly simplistic use concepts and operationalizations make it unclear how mHealth use facilitates behavior change. We argue that these research limitations are hindering an understanding of how mHealth can adapt to a user's changing behavior to facilitate both use and subsequent behavior change.

First, most of the reviewed research only briefly mentions SCT to justify the inclusion of mHealth features (i.e., self-monitoring, goal-setting, feedback, social comparison, and social support features). It is rare that studies hypothesize about and test theoretical relationships proposed by SCT. Some studies test SCT by evaluating relevant constructs as a result of an mHealth intervention. These studies find either no effect or only small effects of mHealth on SCT constructs and show inconclusive results regarding behavior change (Choi et al. 2016; Fanning et al. 2017; Liu and Willoughby 2018; Romeo et al. 2021; Voth et al. 2016; Zhou et al. 2016). Furthermore, almost none of the reviewed research considered self-regulatory feedback loops of behavior change as a dynamic within-person process that helps individuals pursue health-related goals over time, which is a main tenet of SCT. An exception is the study by Koreinik et al. (2018), who adapt step-goals based on an individual's current behavior. Instead, the vast majority of research simply includes features for self-regulation (e.g., self-monitoring, goal-setting, and feedback) without considering its dynamic nature. These studies do not preclude the dynamics of self-regulation. However, they ignore that self-regulation is a dynamic process influenced by changing social, environmental, and personal factors (Bandura 1991). The lack of theoretical grounding is hindering the ability to understand what dynamic psychological processes occur during goal pursuit and when mHealth can best support users.

Second, a majority of the experimental designs in the reviewed mHealth research are not adequate for assessing whether specific mHealth features have the intended immediate effects (e.g., on mHealth use), when a particular mHealth feature should be delivered, and how within-person dynamic processes underly behavior change. The vast majority of the reviewed research uses a randomized controlled trial (RCT) or randomized trial (RT) design. These study designs assign individuals to an mHealth intervention and attribute differences in outcomes to the intervention at a distal point in time. Traditional RCTs (i.e., mHealth versus no mHealth) are not designed to investigate *when* specific mHealth features are most effective at impacting use or behavior (Arigo et al. 2019; Klasnja et al. 2015). Instead, they aim to assess *whether*, on average, mHealth as a whole has an effect on behavior. RTs can assess the effectiveness of individual features. For example, an RT can compare the effects of an app with social features to one with reward features and the impact on behavior at a distal point in time. Fanning et al. (2017) show that an app that rewards users with points and badges increases physical activity behavior significantly more compared to an app with only goal-setting features. King et al. (2016) show that an app with social features increases physical activity behavior significantly more compared to an analytic app with goal-setting features and an affective app with features for receiving rewards and points. However, RCTs and RTs cannot investigate the immediate impacts of specific features on mHealth use because they assess the entire mHealth app and the effects at a distal point in time. Moreover, these study designs cannot account for within-person dynamic processes because they use a between-subject design. More advanced study designs, such as MRTs, can overcome these limitations. For example, researchers can identify the most appropriate time to push goal feedback or social feedback messages to users and can better understand the impact on immediate mHealth use and subsequent behavior change. Moreover, an MRT with a within-person design can account for within-person processes that are known to occur during goal pursuit. However, not a single study in our review used an MRT design. The only study in our review that was designed to explicitly account for dynamic processes implied by SCT employed a system ID open loop experiment to pseudo-randomly assign adaptive step-goals (Korinek et al. 2018). The design considers that on any given day, individuals vary regarding if they consider goals to be ambitious, doable, or ambitious but still doable.

Third, overly simplistic use concepts make it difficult to understand to what extent mHealth use impacts behavior. Most research looks at system use to infer the impact on behavior. For example, binary use concepts are often employed, in which one group receives an mHealth app and is compared to a group that receives no mHealth app or a non-digital analog intervention (e.g. use vs. non-use). Other research looks at the extent of use to infer the magnitude to which mHealth use impacts behavior (e.g. measuring the time spent in app or counting app logins). These mHealth use concepts are problematic because mHealth use is treated as a black box. It is difficult to tease apart effects of single features and their interactions because use is conceptualized as use of the system as a whole. A better approach would be to conceptualize mHealth use as user interactions with mHealth features that can facilitate behavior change (Fallon et al. 2019). Some studies examine such use interactions. For example, some ask participants to self-report which features were most beneficial (Fanning et al., 2016; Torquati et al., 2018), providing information on feature use at a single point in time. Other studies use objective trace data to measure specific use interactions and look at use of social features (Al Ayubi et al. 2014; King et al. 2016) or self-monitoring features (Liu and Willoughby 2018; Voth et al. 2016), providing detailed information on feature use over time. Such objective and specific mHealth use concepts have the potential to open up the black box of mHealth use, provide a theory-grounded concept of mHealth use, and demonstrate more precisely when users interact with mHealth features and if their use has the intended effects on behavior change. Accordingly, objective feature use concepts can better explain dynamic user interactions over time.

Social Cognitive Theory

There are various psychosocial models and theories that can inform how mHealth use facilitates behavior change including the health belief model (Rosenstock 1960), the theory of planned behavior (Ajzen 1991), the theory of reasoned action (Fishbein and Ajzen 1975), and protection motivation theory (Rogers 1975). These theories aim to understand behavior based on static snapshots of human behavior. SCT, however, considers ongoing, dynamic feedback loops of behavior in response to changing social, personal, and environmental states (Bandura 1991), which rival theories do not consider. The dynamic processes proposed by SCT (i.e., self-regulation; the changing impact of social, environmental, and personal factors on self-regulatory feedback loops; and the triadic reciprocal relationship between these factors) are what make SCT unique in predicting and explaining behavior change (Beauchamp et al. 2019).

According to SCT, self-regulation is particularly important for behavior change (Bandura 1991; Beauchamp et al. 2019). It is a dynamic discrepancy-reducing feedback loop in which individuals set goals as a reference and compare their present state to their desired goal-state (Carver and Scheier 1982). Based on the discrepancy between progress towards the goal and the desired end state, individuals are motivated to further pursue their goals (Bandura 1991). Accordingly, self-regulation of behavior is an ongoing, dynamic, within-person process that varies over time based on how much progress one has made towards their goals.

SCT proposes that self-regulation of behavior is shaped by changing social and environmental states (Bandura 1991). Consequently, cues can directly influence behavior during goal pursuit (Bandura 1991). Cues can be internal (i.e. self-generated) or external (i.e. from the environment). Internal cues can refer to motivation self-generated from *goal feedback*. For example, goal feedback provides information on a personal goal and one's performance towards that goal, which activates motivation to reach the goal (Bandura 1991). External cues can refer to motivation from *social feedback*, such as social support or social comparison (Bandura 1991). Social feedback provides external support for adherence to personal standards during goal pursuit (Bandura 1991). Both goal feedback and social feedback can occur incidentally (e.g. a friend telling you they went for a run) or deliberately (e.g. a push notification telling you your goal progress). Accordingly, SCT proposes that goal feedback and social feedback will be important for the continuation of self-regulation of behavior. The relationship between behavior, the environment, and personal factors in SCT is explained by reciprocal determinism, in which all three elements bidirectionally interact and dynamically shape one another (Bandura 1991). This bidirectionality means that the environment can motivate behavior and one's behavior can simultaneously shape perceptions of the environment.

In summary, SCT postulates various dynamic feedback loops between an individual's thoughts, the environment, and behavior that continuously occur over time to predict and explain behavior change. However, while SCT provides strong theoretical reasons for feedback cues and the bidirectional relationship between behavior, the environment, and personal factors, it provides little guidance on the time lagged effects. For example, it is unclear if the effects of the environment on behavior remain constant throughout goal pursuit or whether they vary during goal pursuit (Riley et al. 2011). A core difference is that SCT specifies that a dynamic bidirectional relationship exists, but it does not specify how that relationship behaves over time (Spruijt-Metz et al. 2015). Accordingly, it is unclear when and under what circumstances goal and social feedback are most effective at impacting behavior.

Goal Pursuit

Research on goal pursuit builds on the dynamic self-regulation process specified in SCT and provides reasons why goal feedback and social feedback might be more or less effective at different stages of goal pursuit. We build on the dynamic processes proposed by SCT by understanding the different psychological processes that occur at the beginning, middle, and end stages of goal pursuit. An overview of these psychological processes and appropriate feedback messages is displayed in Figure 1 and explained below.

When individuals are in the beginning stage of goal pursuit and their level of progress is low, they focus on whether they can attain their goal and ask the question "Can I get there?" (Huang and Zhang 2011). Thus, motivation stems from the attainability of the goal and users' perception of goal attainability. Because in the beginning stage of goal pursuit the distance to the end-state of the goal is so large, it provides little information on making the goal seem attainable (Koo and Fishbach 2012). Instead, in the beginning stage of goal pursuit, individuals use the initial state as a reference on goal progress because it distracts from the fact that they are so far away from attaining their goal (Koo and Fishbach 2012). Accordingly, goal feedback that emphasizes the goal attainability will be beneficial in the beginning stage of goal pursuit. More specifically, goal feedback that emphasizes the completion of subgoals can to an even greater extent help individuals perceive the goal as attainable (Huang et al. 2017; Nunes and Drèze 2006). Subgoals are structured as smaller and more manageable steps towards the overall goal. For example, an overall weekly goal can be broken down into smaller and more manageable daily subgoals. As such, *goal feedback* which emphasizes the completion of smaller *subgoals* is expected to make individuals perceive their overall goal as attainable and will be especially valuable in the beginning stage of goal pursuit.

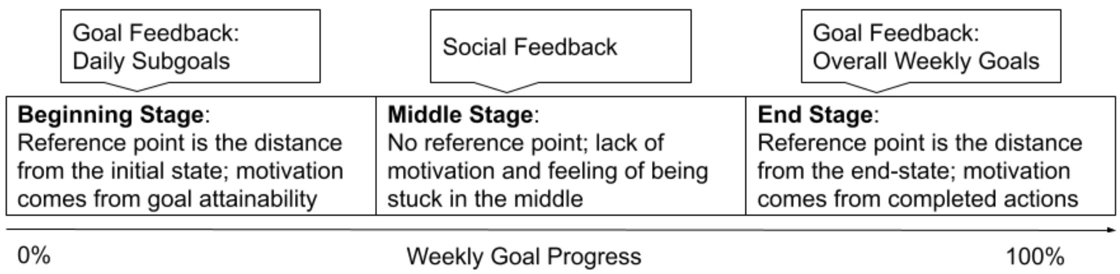


Figure 1. Feedback Messages and Psychological Processes During Stages of Goal Pursuit

In the middle stage of goal pursuit, users lack an appropriate reference point because they are too far from both the initial state and the desired end state (Bonezzi et al. 2011). Thus, individuals cannot focus on a reference point that would make their subsequent actions appear more impactful, regardless of the goal feedback (Bonezzi et al. 2011). This results in motivational lapses that occur about halfway to the goal's end state where individuals often feel stuck in the middle of goal pursuit (Bonezzi et al. 2011). Thus, instead of goal feedback at the middle stage of goal pursuit, *social feedback* with information on how others are performing and how others view one's performance can provide additional motivational benefits. Due to these motivational benefits, *social feedback* can actually restore motivation to pursue goals in the middle stage of goal pursuit (Huang 2018).

When individuals have achieved sufficient progress toward the goal and are relatively certain about its attainability, they shift their focus to the temporal aspect of goal attainment and become more concerned about the question "When will I get there?" (Huang and Zhang 2011). To answer this question, individuals monitor progress based on the distance to the desired end-state. The reference point helps them perceive that their actions are of value for achieving their goal (Bonezzi et al. 2011; Huang and Zhang 2011). Accordingly, goal feedback that emphasizes how close one is to achieving their overall goal will be beneficial at the end stage of goal pursuit. As such, *goal feedback* which emphasizes the completion of the *overall goal* is expected to be especially beneficial at the end stage of goal pursuit (Huang et al. 2017). Conversely, subgoals will not be beneficial at the end stage because they attenuate the ease of visualizing the end state.

In summary, mHealth has the capability to track individuals' goal progress in real-time and make internal and external cues more salient at the most appropriate stage of goal pursuit. However, our review of mHealth literature for physical activity that uses an SCT perspective shows that mHealth largely ignores the dynamics of self-regulation and study designs are not sufficient for understanding these within-person dynamics. SCT provides theoretical reasons why self-regulation is important for behavior change, how reciprocal determinism influences behavior, and why certain cues can further encourage self-regulation of behavior. However, it is unclear how the relationship behaves over time. We build on this dynamic self-regulatory feedback loop by identifying when social and goal feedback are most effective during goal pursuit and how this impacts immediate mHealth use and subsequent physical activity behavior.

Research Model and Hypotheses Development

In this research, we investigate under what circumstances messages can trigger self-regulatory processes and aim to address the existing research limitations in mHealth literature that use an SCT perspective (no dynamic perspective, lack of sophisticated experimental designs, and lean use concepts). As SCT posits, goal feedback and social feedback act as cues to foster self-regulatory behavior. The operationalization in our setting is push notifications with goal or social feedback content, which are hypothesized to lead to use of mHealth features. Based on literature on goal pursuit, we expect the effect of goal and social feedback on mHealth use to behave differently at different stages of goal pursuit. To test these dynamic effects, we distinguish between goal feedback messages regarding subgoals (daily goals), overall goals (weekly goals), and no goal feedback. Regarding social feedback, we distinguish between sending social feedback and not sending social feedback. Based on the different psychological processes that occur during goal pursuit, we propose that the content in the message will be more or less effective depending on if the user is in the beginning, middle, or end stage of goal pursuit. We have conceptualized our research model in Figure 2.

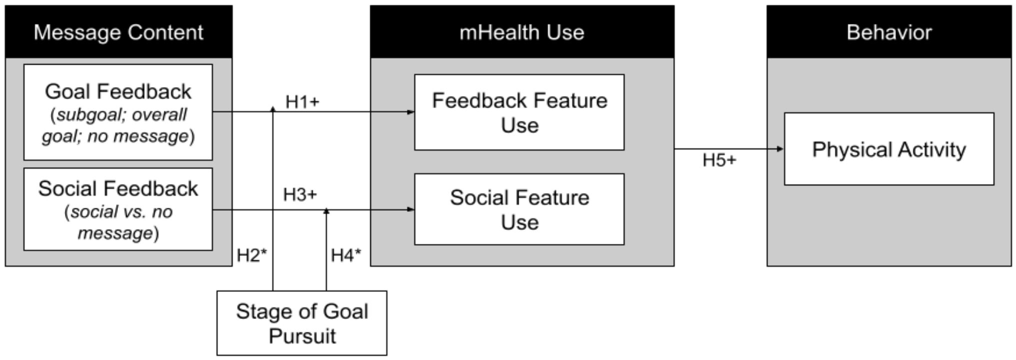


Figure 2. Research Model

In our study, a goal feedback message contains information regarding the extent to which an individual has accomplished his/her daily physical activity goal (subgoal) or weekly physical activity goal (overall goal). The message, thus, contains information on one's goal progress, which is needed for self-evaluating progress towards goals (Bandura 1991). We propose that information on goal progress will influence use of the mHealth feedback feature. Feedback provides dynamic and continuous information on one's behavior while it is in progress (Bandura 1991). Feedback features in mHealth allow users to evaluate their progress towards their physical activity goals by comparing current behavior to goal behavior with graphs or charts (Fallon et al. 2019). Therefore, we hypothesize:

H1: Feedback feature use will be higher immediately after receiving a goal feedback message (subgoal or overall goal) compared to receiving no goal feedback message.

More specifically, we propose that goal feedback messages emphasizing progress on daily subgoals will be most effective in the beginning stage of goal pursuit. In early stages of goal pursuit, people derive motivation primarily from the belief that the goal is attainable (Zhang and Huang 2010). However, when individuals first start to pursue a goal, they experience high uncertainty about whether they can ultimately attain the goal (Koo and Fishbach 2008). A focus on subgoals is expected to help individuals perceive the goal as attainable. Subgoals can reframe an overall goal to make it seem smaller and more manageable, which also makes it seem more attainable (Huang et al. 2017; Nunes and Drèze 2006). Accordingly, a message that focuses on the completion of a daily physical activity subgoal can make one perceive that the overall weekly goal is indeed attainable. Therefore, we hypothesize:

H2a: Goal feedback messages emphasizing daily subgoals will be most effective at impacting feedback feature use in the beginning stage of goal pursuit.

Additionally, we propose that goal feedback messages emphasizing progress on the overall weekly goal will be most effective at the end stage of goal pursuit. As individuals make progress towards their goal and are approaching the end stage of goal pursuit, they shift their focus away from the goal's attainability and onto the reduction of the remaining discrepancy between their current position and the final goal (Koo and Fishbach 2008). This shift in focus helps them to perceive that their actions are of value for achieving their goal (Huang et al. 2017). As such, a message that focuses on the overall goal helps individuals attribute their goal progress to their completed actions because the accumulated progress makes the goal-directed actions appear more valuable (Huang et al. 2017). However, at the end stage of goal pursuit, subgoals hinder the possibility to imagine the end-state of the overall goal (Huang et al. 2017). For these reasons, we propose that a goal feedback message that focuses on overall weekly physical activity goals will be especially valuable at the end stage of goal pursuit, which will be reflected in more feedback feature use following the delivery of the overall weekly goal feedback message. Therefore, we hypothesize:

H2b: Goal feedback messages emphasizing overall weekly goals will be most effective at impacting feedback feature use at the end stage of goal pursuit.

SCT specifies how external cues, such as social feedback, can impact behavior through social comparison and social support (Bandura 1991). Social comparison facilitates a judgement process, in which people compare their performances to others. The information on others' behaviors initiates self-comparisons and the motivation to perform better than others (Bandura 1991). Social support provides collective support for adherence to moral standards in which individuals are encouraged by praise and recognition (Bandura 1991). In mHealth, we propose that when users receive a push notification with information regarding social feedback, this will trigger the use of social features. For example, when users receive a message about their rank and physical activity behavior in comparison to others on a leaderboard, this will initiate the desire to self-compare their behavior with other users and users will open the leaderboard feature. Similarly, when users receive a message that others have commented or liked their physical activity behavior, they will experience a sense of encouragement and will be more likely to interact with the social feed feature. Therefore, we hypothesize:

H3: Social feature use will be higher immediately after receiving a social feedback message compared to receiving no social feedback message.

Social feedback can be especially valuable in the middle stage of goal pursuit. In the beginning and end stages of goal pursuit, individuals leverage reference points regarding their own performance (Koo and Fishbach 2008, 2012). However, in the middle stage of goal pursuit, individuals lack an appropriate reference point because they are too far from both the initial phase and the end goal (Bonezzi et al. 2011). Therefore, a social feedback message will be most valuable to users in the middle stage of goal pursuit (e.g. achieved 50% of their goal). In fact, viewing social feedback regarding others' performance enhances individuals' drive to continue goal pursuit (Huang 2018). However, the same effect does not occur at the beginning or end stages of goal pursuit (Huang 2018). Therefore, when a social feedback message is provided to users, we propose that it will be most effective at increasing social feature use in the middle stage of goal pursuit. At this stage, the social feedback message will act as an artificial reference point and an additional motivational source. Conversely, in the beginning and end stages of goal pursuit, the social feedback message will not be as effective at increasing social feature use because users already utilize their own reference points as a motivational source. Therefore, we hypothesize:

H4: Social feedback messages will be most effective at impacting social feature use in the middle stage of goal pursuit.

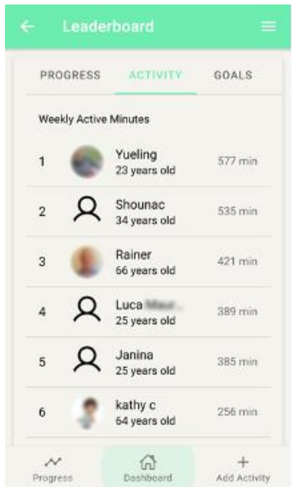
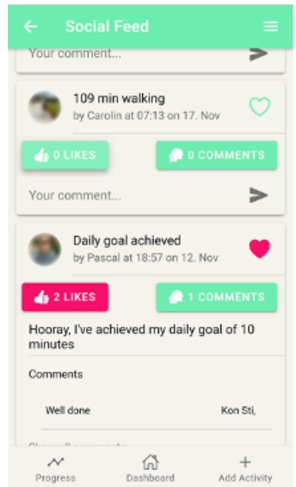
Use of mHealth features for self-regulation are expected to impact behavior change. Consistent with SCT, self-regulation is core to behavior change (Bandura 1991). Moreover, social interactions are expected to further encourage self-regulation of behavior (Bandura 1991; Fallon et al. 2019). Therefore, we propose that with both more feedback feature use and social feature use, users will also increase their physical activity behavior. Additionally, consistent with literature on IS use, we propose that more effective use of the technology (i.e., interactions with social features and feedback features) will positively impact outcomes of use (Burton-Jones and Grange 2013). Therefore, we hypothesize:

H5: An increase in mHealth use leads users to be more physically active.

Methods

YouMove App Development

Addressing the need for a better scientific understanding of mHealth apps and to test the above-mentioned hypotheses, YouMove, a physical activity app, was developed. The development of an app was considered necessary to be able to have access to the data and full control over the data collection process. The developed app guarantees the suitability for scientific studies and opens the opportunity for new research designs. It aims at helping users to become more physically active and lets users record their activity and observe their progress towards daily and weekly physical activity goals. The initial goal value for all users is based on the World Health Organization (WHO) recommendation of at least 150 active minutes per week (WHO 2020). Users could adjust their daily and weekly goals at any time to make them more difficult or more achievable. Consistent with WHO (2020), activities are distinguished with two intensities: Moderate activity for activities like walking, chores, or cycling; and Vigorous activities such as running, weight training or soccer. Exemplary screenshots of the app are shown in Table 2.

Feedback Feature	**Social Features**		**Physical Activity Tracking**
	Leaderboard	**Social Feed**	
			
Table 2. Screenshots from YouMove App			

YouMove and its features were developed based on SCT. The *dashboard* allows users to access the core features of YouMove. The *feedback feature* allows users to visually see their progress towards weekly and daily goals through a graph and provides a list of previous activities. *Physical activity tracking* allows users to record their activities live with a stopwatch or enter them manually. YouMove also synchronizes activities from native health apps, such as Apple Health and Google Fit. The *leaderboard* allows users to compare with others on weekly active minutes, percentage of goal progress, and number of goals achieved. The *social feed* allows users to see, like and comment on posts of others. New activities and goal achievements are automatically posted to the social feed. The *user profile* can be viewed by other app users and contains the user's name, picture, profile description, goal progress, and recent activities.

The synchronization with Apple Health and Google Fit allows users to effortlessly track their activities as these apps automatically detect activities. Consequently, users only have to manually enter activities that are not recorded by these apps (e.g., because the user did not carry their phone with them). A key feature of the app is that it tracks all user interactions with trace data, such as time spent in different features, number of posts, likes and how often the user opened the app. YouMove was developed in TypeScript using the Ionic framework to build an app for Android, iOS and the web from a single code base. Ionic add-ons were used to integrate native health APIs and to be able to send push notifications to users. A web dashboard allowed researchers to monitor the study in real-time. The app's features, functionalities, and data output allowed us to test our research hypotheses in an MRT.

Micro-Randomized Trial

An MRT is a novel research design that aims to identify under which conditions an intervention is the most effective and is well-suited to develop and optimize JITAIs (Klasnja et al. 2015). In an MRT, a set of scenarios are defined, consisting of intervention options and a specific user state. The effectiveness of the intervention options, given the specific user state, is analyzed. Every time a specific state occurs, the participant is then randomized to an intervention option. This is called a decision point. Intervention options can be providing a treatment versus not providing a treatment in the simplest case. They can also contain different variants of a treatment. Participants are repeatedly randomized to the intervention options at each decision point and the outcomes are measured. As a result, the effectiveness of an intervention option in a certain state can be contrasted with other intervention options or states. This information can then inform a JITAI, because it identifies which type of intervention is the most successful under which circumstances. MRTs further distinguish between a proximal outcome, which is the direct and immediate effect of an intervention, and the distal outcome, which is the long-term goal of the intervention and is hypothesized to be achieved by a repeated number of proximal outcomes. For more information on MRTs, please refer to Klasnja et al. (2015).

Operationalization of Variables and Research Design

In the present study, the effect of feedback messages on app usage and physical activity behavior is investigated. Through increasing app usage as a proximal outcome, participants are expected to become more physically active in the long-term (distal outcome). Two scenarios were used and are presented in Table 3. In the first scenario, at a given time in the evening users were randomized to receive a push notification containing feedback on their daily goal, their weekly goal, or no push notification with equal probability (p=.33 for each). As a proximal outcome, the feedback feature use in the 60 minutes after receiving the notification was captured. In the second scenario, at three given times during the day users were randomized to receive a push notification containing social feedback or no push notification with equal probability (p=.5 for each). As a proximal outcome, the social feature use in the 60 minutes after receiving the notification was captured. To ensure users were generally available to receive a push notification, users specified the times they want to receive push notifications for both scenarios when they created an account for the app. This was used as the decision point for randomizing users to receive a message. All times had to be spaced three hours apart from each other to enable us to ensure a distinct mapping to one notification. Stage of goal pursuit was determined based on the user's relative progress towards the weekly goal and was objectively captured via the app at the time of the decision point. The relative progress towards the goal was then coded as the beginning, middle, or end stage of goal pursuit.

Scenario	Decision Point / User State	Intervention Options	Message Content	Proximal Outcome	Distal Outcome
Goal Feedback	Time of day: 1 user specified time slot Stage of Goal Pursuit: objectively captured via the app; coded based on weekly goal progress: 0 (beginning): 0%-33% 1 (middle): 34%-66% 2 (end): 67%-100%	Daily subgoal feedback	*You have reached X% of your daily goal, with Y% to go!*	Feedback feature use 60 minutes following push notification	Minutes of physical activity
		Weekly overall goal feedback	*You have reached X% of your weekly goal with Y% to go!*		
		No feedback	n/a		
Social Feedback	Time of day: 3 user specified time slots Stage of Goal Pursuit: objectively captured via the app; coded based on weekly goal progress: 0 (beginning): 0%-33% 1 (middle): 34%-66% 2 (end): 67%-100%	Social feedback	*Check out the leaderboard to see how you compare to others. / Your post was liked by someone. Go check it out!*	Social feature use 60 minutes following push notification	
		No feedback	n/a		

Table 3. Operationalization of Variables

The dependent variables for the proximal outcome were time deltas indicating the duration users spent on different features in the application. The distribution of these variables was highly skewed. Therefore, these were log transformed after adding 0.1 to avoid logarithms of 0. At the decision points, effects were measured on the time frame of 60 minutes following the notification. 60 minutes was chosen as the proximal outcome time frame for practical reasons, because it is a trade-off between a too short time frame which bears the risk that the user does not see the push notification and a too long time frame which bears the risk that the behavior is caused by factors other than the notification (Klasnja et al. 2015). Usage time in the preceding 60 minutes served as a control variable because it was assumed that if users spent time in a specific feature before the notification, they would be less interested in checking this feature again after the notification. The dependent variable for the distal outcome was minutes of physical activity, which was either automatically pulled from the Google Fit or Apple Health API or manually entered by participants.

The research design and measurement of variables was pretested with a sample of 35 participants to ensure feasibility and improve the user experience. The app was adapted accordingly following the pre-test. The adaptions included bugfixes and improved activity tracking. Based on a power analysis for MRTs (Seewald et al. 2016), 67 participants were invited to take part in the study through announcements in an Information Systems lecture at a university in Europe. Participants were compensated with a 15 Euro Amazon gift card for taking part in the study. Participants who registered for the study consented to the study procedure, filled out a pre-survey, downloaded the app, and set up an account during which they provided demographic information. The study duration was four weeks (28 days). After completion, participants completed a post-survey inquiring about previous experience with physical activity apps and physical activity levels.

Data Analysis

For the main data analysis, multilevel models (MLMs) can be considered as an appropriate choice due to their resemblance to MRTs since both include between-subjects as well as within-subject factors. MLMs as well as generalized estimating equations (GEE) however can be biased when using time-varying covariates and are therefore only of limited use for analyzing MRT data (Qian et al. 2020). Boruvka (2018) developed a weighted, centered least-squares (WCLS) estimator for the analysis of MRTs that can deal with time-varying covariates and consistently estimates the causal treatment effect. This WCLS estimator was used for the present study. To obtain the estimator, the geepack R package (Højsgaard et al. 2019) was employed as follows: We (1) set the weights of the data points to the availability, (2) chose a working independence correlation structure, and (3) centered the treatment variable with the randomization probability to yield the desired estimator (Qian et al. 2020).

The general model of the WCLS estimator is:

$$Y_{t+1} \sim I_t(\alpha_{10} + \alpha_{11}S_t + (A_t - p)\beta_1)$$

with Y_{t+1} being the estimated proximal outcome of the next decision point, I_t being the participants availability, S_t being the control variables, A_t being the treatment indicator, and p being the probability of delivering a treatment (randomization probability). For H1, Y_{t+1} was the feedback feature use in the 60 minutes after the decision point t. S_t contains the feedback feature use before decision point t. A_t is the delivery of a goal progress push notification with probability $p = 0.33$ for each type of goal progress message. For H2a and H2b, the same model was used with the addition of stage of goal pursuit to S_t. For H3, Y_{t+1} was the social feature use in the 60 minutes after the decision point t. S_t contains the social feature use before decision point t. A_t is the delivery of a social feedback message with probability $p = 0.5$ for receiving a message or not. For H4, the same model was used with the addition of the stage of goal pursuit to S_t. For H5, Y_{t+1} was the physical activity of a user. $S_t$is the total feedback feature and social feature use. A_t and p were not used for this hypothesis.

Results

Participant Characteristics

Of the invited participants, 61 downloaded and installed the app and therefore were included in the analysis. The average age among app users was 21.69 years (SD=1.76). 64% of participants were female, the most frequent occupation was “student” (95%), and the highest academic degree was A-levels (93%).

The total time spent in the app was 31 hours, amounting to an average of 1 minute and 11 seconds (SD=54 seconds) of use per user per day. The leaderboard was used in total for 485 minutes, the feedback feature for 407 minutes, and the social feed for 167 minutes. The average time spent per view was 11 seconds (SD=27 seconds) for the feedback feature, 23 seconds (SD=58 seconds) for the leaderboard, and 21 seconds (SD=50 seconds) for the social feed.

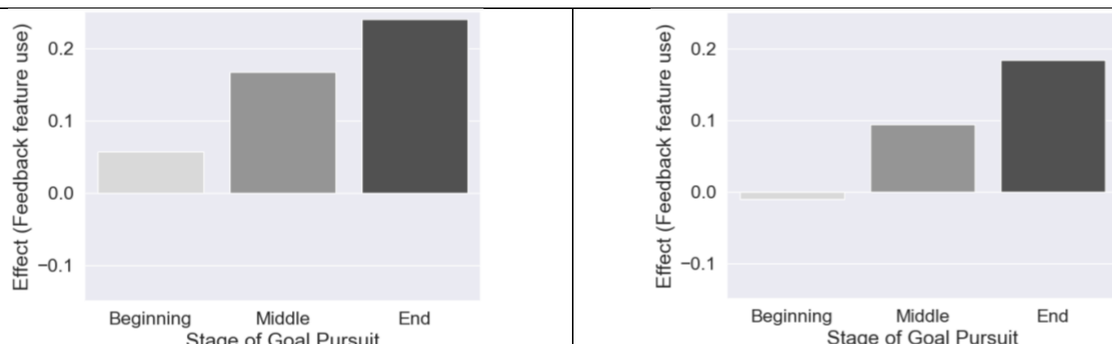
Participants tracked 860 hours of physical activity using the app, which equals an average of 34 minutes (SD=28 minutes) of physical activity per user per day. The highest amount of activities per day among all users was recorded on day 2 (3,525 active minutes) and the lowest on day 27 (938 active minutes). 39% of activities were recorded automatically through Google Fit (23%), Apple Health (12%) or other apps (4%). Average time per activity was 48 minutes (SD=34 minutes) for manually recorded activities, 34 minutes (SD=26 minutes) for Apple Health and 23 minutes (SD=17 minutes) for Google Fit.

General Effects of Feedback Messages

6,160 available decision points were included in the analysis. 1,540 decision points were obtained for goal feedback messages (1 per day per user) and 4,587 decision points for social feedback messages (3 per day per user). In general, goal and social feedback messages impacted the extent of mHealth use (i.e. average time in app). The extent of app use in the 60 min following a decision point across all 6,160 available decision points (goal and social feedback message) was 29 seconds (SD = 277 seconds). Averaging over study days and types of messages, delivering a message (goal and social feedback) versus providing no message increased the extent of app use by 284% (coefficient(b)=1.009, standard error (std. err.)=0.113, $p<0.001$***), or an additional 14 seconds, on average. Providing a message versus providing no message depended on the day of the study (b=-0.09431, std. err.=0.0073, $p<0.001$***), so that with each additional day in the study, the effect of delivering a message on the extent of mHealth use increased by 0.1 %.

Main Data Analysis

The main data analysis used the WCLS estimator and equation as presented in the methods. Feedback feature use was 17% higher after a goal feedback message was delivered (coefficient(b)=0.070, standard error (std. err.)=0.02, $p<0.001$***), therefore providing **support for hypothesis 1**. The effect of goal feedback messages depended on the stage of goal pursuit and had a greater effect the more progress the user made (b=0.036, std. err.=0.010, $p<0.001$***). This is depicted in Figure 3a and 3b. Concerning daily subgoal feedback messages, they did not significantly impact feedback feature use (b=0.025, std. err.=0.024, p=0.293) and the effect did not depend on the stage of goal pursuit (b=0.005, std. err.=0.018, p=0.766), therefore providing **no support for hypothesis 2a.** Weekly overall goal feedback messages, on the contrary, lead to an increase in feedback feature use (b=0.065, std. err.=0.026, p=0.013*). When comparing the effect of weekly overall goal feedback messages across goal stages, it shows that they were 18% more effective at increasing feedback feature use in the end stage than in all other stages (b=0.035, std. err.=0.010, $p<0.001$***), therefore providing **support for hypothesis 2b.** This is depicted in Figure 3b.



a) Daily Subgoal Feedback | b) Weekly Overall Goal Feedback

Figure 3. Effects of Goal Feedback Messages on mHealth Use

Social feature use was 33%, higher after a social feedback message was delivered (b=0.208, std. err.=0.019, $p<0.001$***), therefore providing **support for hypothesis 3**. When comparing the effect of social feedback messages across goal stages, it shows that they were 33% more effective at increasing social feature use in the middle stage of goal pursuit than in all other stages (b=0.208, std. err.=0.065, p=0.001**), providing **support for hypothesis 4**. This is depicted in Figure 4. Last, the proximal outcome, mHealth use, was positively associated with minutes of physical activity (b=0.046, std. err.=0.006, p=0.001***), providing **support for hypothesis 5**.

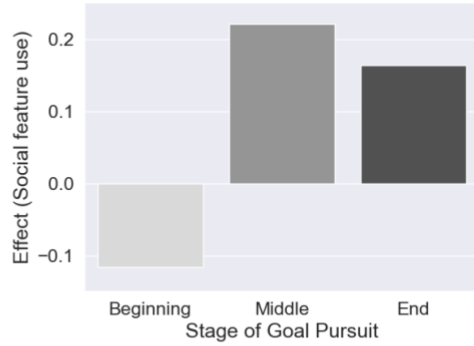


Figure 4. Effects of Social Feedback Messages on mHealth Use

Discussion

Principal Findings

In this study, we aimed to better understand the effectiveness of mHealth in changing individuals' physical activity behavior by focusing on the content of messages (social feedback and goal feedback) sent at various stages of goal pursuit (beginning, middle, and end) and the impact on mHealth use. Our findings show that the impact of goal and social feedback messages on mHealth use is to some extent driven by the message content and the user's stage of goal pursuit. Generally, we find that goal progress messages impact feedback feature use (H1) and social feedback messages impact social feature use (H3). More specifically, we do not find evidence that daily subgoal feedback messages are more effective at impacting feedback feature use at the beginning stage of goal pursuit (H2a). However, we do find that social feedback messages are most effective at impacting social feature use at the middle stage of goal pursuit (H4) and goal feedback messages that emphasize weekly overall progress are most effective at impacting feedback feature use at the end stage of goal pursuit (H2b). Moreover, mHealth use contributes to increased physical activity behavior (H5).

Theoretical and Practical Contributions

Our findings yield several theoretical contributions. First, we contribute to SCT by considering the time lagged effects of goal and social feedback. SCT specifies a bidirectional relationship between the environment and behavior (Bandura 1991), but it does not specify how that relationship behaves over time (Spruijt-Metz et al. 2015). We rely on literature on goal pursuit to understand the time lagged effects of goal and social feedback and build on the self-regulatory feedback loops proposed by SCT. We find that the effectiveness of goal and social feedback varies depending on if users are in the beginning, middle, or end stage of their goal pursuit. Thus, the effects of the environment on behavior does not remain constant over time. Instead, the effects vary based on one's stage of goal pursuit. Our findings are consistent with the bidirectional relationships proposed by SCT. We show that cues from the environment impact behavior and, simultaneously, behavior (i.e., progress towards goals) impacts how one perceives those cues. We contribute to SCT by elaborating on how goal and social feedback impact self-regulation over time.

Second, we contribute to research on IS use. Most prior mHealth research considered mHealth use as binary (present or absent) or as the extent of use (time in app). These superficial use concepts measure use of the system as a whole and are not well-suited for understanding dynamic use behavior (Burton-Jones et al. 2017) or how users interact with the technology (Burton-Jones and Straub 2006; Fallon et al. 2019). In this study, use was conceptualized as interactions with specific mHealth features that vary based on one's stage of goal pursuit. These use interactions were captured through objective trace data. The findings indicate that goal feedback messages have an immediate impact on use of feedback features and social feedback messages have an immediate impact on use of social features. Moreover, the effects on use are not constant, but rather vary as one progresses towards their goals. Therefore, our findings illustrate that a dynamic use concept provides more information about how, why, and when feedback messages impact use. We theorize about how and why goal and social feedback impact mHealth use by using the dynamic feedback loops proposed by SCT. We theorize about when goal and social feedback are most effective at impacting mHealth use by using literature on goal pursuit. The results indicate that mHealth use is a dynamic process shaped by both environmental cues and one's progress towards their goals. Furthermore, our findings also show that use of feedback and social features results in increased physical activity behavior. These results build upon the premise that effective use of IS can increase outcomes of use (Burton-Jones and Grange 2013).

Third, we contribute to mHealth and IS literature by employing an experimental design for studying dynamic use concepts and feedback loops for behavior change. Currently, mHealth research mainly employs RCTs, which are not adequate for understanding how mHealth features immediately impact use and dynamic feedback loops that underly behavior change. We employ an MRT design that helps reveal how feedback loops operate over time and how mHealth features that embody theoretical constructs, such as goal and social feedback, impact these relationships. We propose that an MRT study design will be an instrumental tool for IS researchers aiming to understand dynamic use concepts. Moreover, an MRT design will be useful to mHealth researchers aiming to understand bidirectional relationships between the environment, personal factors, and behavior and how these relationships behave over time.

Our research findings also yield several practical contributions. Given that our results indicate that use of feedback and social features significantly impacts physical activity behavior, mHealth app developers should focus on how to trigger use of these mHealth features. We provide two ways to do this. The first is by sending goal feedback messages and the second is by sending social feedback messages. Our findings also highlight the importance of the timing of feedback messages, especially with regards to social messages and overall weekly goal progress messages. We demonstrate that social feedback is most effective at increasing social feature use in the middle stage of goal pursuit and overall weekly goal progress is most effective at increasing feedback feature use at the end stage of goal pursuit. App developers should consider both the content and timing of push notifications to ensure their impact on mHealth use and behavior.

Limitations and Future Research

Our results offer several avenues for future research. The most apparent area for future research is to understand what message content impacts mHealth use in the beginning stage of goal pursuit. We do not find support for H2a, which stated that daily subgoal feedback messages would be most effective at increasing feedback feature use in the beginning stage of goal pursuit. In general, we find that a goal feedback message (subgoals and overall goals) leads to more feedback feature use with increasing weekly goal progress. Research on goal pursuit emphasizes the importance of goal attainability in the beginning stage of goal pursuit (Huang et al. 2017). Therefore, our hypothesis development focused on ensuring that the goal feedback message highlighted goal attainability by breaking the overall goal into smaller and more manageable subgoals. However, what we did not account for was potential carry-over effects of goal attainment from the previous day or week. As other research suggests, achieving or not achieving one's goal in a previous time period in a repeated goal setting can influence motivation in the subsequent day or week (Koo and Fishbach 2010). As such, goal attainment in the previous day or week could impact one's perception of goal attainability on the current day. Therefore, future research can consider how to account for goal attainment in a repeated goals setting, which might explain the null finding. Additionally, getting individuals to continue to use mHealth and balancing the right amount of push notifications to encourage use is an ongoing problem. Our results show that mHealth use declines over time. Similarly, while our research focuses on the advantages of push notifications, other research streams show disadvantages, such as task interference (Jenkins et al. 2016), distraction (Throuvala et al. 2021), and technostress (Galluch et al. 2015). In future research, an MRT could be used to better understand both the immediate positive and negative effects of push notifications and how their impact changes over time. A potential opportunity for future research is to understand when to fade out push notifications to avoid potential negative effects. Also, while our study focused on adapting the content of messages based on a user's stage of goal pursuit, future research can leverage different functionalities of mHealth technology. For example, live GPS can also be used to adapt message content based on a user's location or the weather. Future research can use an MRT design to further improve the effectiveness of push notifications and the impact on mHealth use. Last, the generalizability of our results depends partly on the representativeness of our sample. We used a student sample, which is appropriate if clearly articulated and justified (Compeau et al. 2012). A student sample matched our research goals because younger educated adults are the largest group of mHealth users

(Carroll et al. 2017). Thus, our results are relevant for a large majority of mHealth users. Nonetheless, not all characteristics of college students may transfer to other social groups. Consequently, our work should be replicated in other demographic, cultural, and occupational contexts to increase the generalizability.

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