USING GOAL-SETTING AND FEEDBACK NOTIFICATIONS TO INCREASE PHYSICAL ACTIVITY OUTCOMES

A Sequential N-of-1 Study Using the Precious App

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Master's Thesis in Sports and Exercise Psychology
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Spring 2024

TIIVISTELMÄ

Cuba Villegas, M. 2024. Tavoitteen asettelun ja palautteen hyödyntäminen puhelimen ilmoituksissa fyysisen aktiivisuuden edistämiseksi. Liikuntatieteellinen tiedekunta, Jyväskylän yliopisto, Fyysisen harjoittelun ja liikunnan psykologian pro gradu -tutkielma, 30 s.

Fyysinen passiivisuus on merkittävä riskitekijä ei-tarttuville sairauksille maailmanlaajuisesti, sillä 27,5 % aikuisista ei saavuta suositeltuja liikuntaohjeita. Älypuhelimet tarjoavat skaalautuvan ja kustannustehokkaan keinon laajamittaisiin liikuntainterventioihin. Tämä tutkimus tutki älypuhelinilmoitusten vaikutusta liikuntatuloksiin.

Tutkimukseen osallistui kuusi osallistujaa Helsingistä, Suomesta, joita seurattiin 44 päivän ajan Precious-sovelluksella ja aktiivisuusrannekkeilla. Käytettiin yksilönsisäistä satunnaistettua kontrolloitua koeasetelmaa, jossa osallistujat satunnaistettiin neljään eri tilaan: ei ilmoituksia, tavoiteasetteluilmoitukset, käyttäytymispalautteilmoitukset ja näiden yhdistelmä. Tutkimuksen tavoitteena oli arvioida näiden ilmoitusten vaikutuksia päivittäisiin askelmääräihin, tavoiteasettelukäyttäytymiseen ja tavoitteiden saavuttamiseen.

Tulokset osoittavat, että tavoiteasetteluilmoitukset lisäsivät joidenkin osallistujien todennäköisyyttä asettaa tavoitteita, kun taas käyttäytymispalautteilmoitukset osoittivat myös potentiaalia tässä suhteessa, vaikka laajempien otosten lisävahvistusta tarvitaan. Kumpikaan ilmoitustyyppi ei merkittävästi vaikuttanut päivittäisiin askelmääräihin, ja rajoitetut tietojen saatavuus rajoittivat niiden vaikutuksen arviointia tavoitteiden saavuttamiseen.

Kaiken kaikkiaan tulokset viittaavat siihen, että vaikka tavoiteasettelu- ja käyttäytymispalautteilmoitukset voivat parantaa tavoiteasettelukäyttäytymistä joillakin henkilöillä, niiden kokonaisvaikutus fyysiseen aktiivisuuteen voi olla rajallinen.

Avainsanat: fyysinen aktiivisuus, askeleet, älypuhelinilmoitukset, tavoiteasettelu, palaute, satunnaistettu kontrolloitu koe, yksilönsisäiset vaikutukset, monitasomallinnus.

ABSTRACT

Cuba Villegas, M. 2024. Using goal-setting and feedback notifications to increase physical activity outcomes. Faculty of Sport and Health Sciences, University of Jyväskylä, Master's Thesis, 30 pp.

Physical inactivity is a significant risk factor for noncommunicable diseases globally, with 27.5% of adults failing to meet the recommended physical activity guidelines. Smartphones offer scalable and cost-effective means for widespread physical activity interventions. This study explored the impact of smartphone notifications on physical activity outcomes.

The study involved six participants from Helsinki, Finland, monitored over 44 days using the Precious app and activity bracelets. A within-person randomized controlled trial design was employed, with participants randomized into four conditions: no notifications, goal-setting notifications, behavioral feedback notifications, and a combination of both. The study aimed to assess the effects of these notifications on daily step counts, goal-setting behavior, and goal achievement.

Results indicate that goal-setting notifications increased the probability of goal-setting for some participants, while behavioral feedback notifications also demonstrated potential in this regard, though further validation with larger samples is warranted. Neither type of notification significantly affected daily step counts, and limited data availability restricted the assessment of their impact on goal achievement.

Overall, the findings suggest that while goal-setting and behavioral feedback notifications may enhance goal-setting behavior in some individuals, their overall impact on physical activity may be limited.

Keywords: physical activity, steps, smartphone notifications, goal-setting, feedback, randomized controlled trial, within-person effects, multilevel modeling.

ABBREVIATIONS

app	smartphone application
BCT	behavior change technique
CI	confidence interval
PA	physical activity

CONTENTS

1 INTRODUCTION AND LITERATURE REVIEW

Physical inactivity is one of the leading factors for noncommunicable diseases worldwide (World Health Organization, 2010, p. 7). Global estimates indicate that 27.5% of adults do not meet the recommended physical activity (PA) guidelines for maintaining good health (Guthold et al., 2018). Given these statistics, substantial advancements in behavior change research and implementation are needed to achieve the WHO's 2030 global PA target of a 15% relative reduction in insufficient PA (World Health Organization, 2013, 2019, 2021).

1.1 Self-regulation to bridge the intention-behavior gap

Over the past decades, considerable research has been devoted to unraveling the psychological constructs associated with health behaviors like PA. Underlying this effort is the assumption that effectively manipulating these constructs could lead to more successful behavior change outcomes (Hagger et al., 2010, p. 63; Nurmi et al., 2016, p. 128).

One such construct, motivation, occupies a central role in several theories and models of behavior (e.g., Ryan & Deci, 2000; Schwarzer, 2008; Heckhausen & Gollwitzer, 1987) as the driving force responsible for the initiation, persistence, direction, and vigor of goal-directed behavior (Colman, 2009). As a result, and depending on the theoretical framework used to elucidate its source, motivation can predict certain aspects of PA behavior.

For instance, in the context of self-determination theory (Ryan & Deci, 2000), autonomous forms of motivation have consistently been shown to be positively associated with PA (Teixeira et al., 2012; Nurmi et al., 2016; Courtney et al., 2021; Reifsteck et al., 2023; Ntoumanis et al., 2021), with identified regulation standing out as the foremost predictor of initial and short-term adoption of exercise among regulation styles, and intrinsic motivation being more predictive of long-term adherence (Teixeira et al., 2012). Conversely, controlled forms of motivation have generally been found to exhibit either neutral or adverse correlations with PA (Ng et al., 2012; Teixeira et al., 2012).

Notwithstanding, motivation, on its own, does not always lead to action (Hagger & Chatzisarantis, 2014; Orbell & Sheeran, 1998; Webb & Sheeran, 2006). Several theories and models are grounded on the premise that behavioral enactment is composed of two different and often disjointed phases (e.g., Schwarzer, 2008; Heckhausen & Gollwitzer, 1987): a motivational phase where motives or intentions to engage in a particular action or behavior are formed, and an implemental phase where the volitional processes to execute these intentions take place (Nurmi et al., 2016, p. 129).

The ensuing intention-behavior gap (Sheeran, 2002; Orbell & Sheeran, 1998) has become a critical point of focus in behavior change research, with self-regulation (Scheier & Carver, 1988) steadily garnering recognition as a promising approach to address this gap.

According to self-regulation theory (Scheier & Carver, 1988), individuals engage in a continuous negative feedback loop where they monitor their current states, compare these to their goals, and make behavioral adjustments to minimize discrepancies. The use of self-regulatory behavior change techniques (BCTs) has consistently been shown to be effective in promoting PA (Michie et al., 2009; Bravata et al., 2007; McEwan et al., 2019; Williams & French, 2011; Laranjo et al., 2021; Olander et al., 2013; Dombrowski et al., 2012).

1.2 Physical activity apps

Smartphones have become an increasingly popular avenue for delivering and monitoring PA interventions. Their integral role and presence in modern everyday life position them as the ideal means for collecting real-time ecological data, enhancing researchers' understanding of the processes underlying behavior and behavior change (Michie et al., 2017, p. 6). Moreover, smartphones provide scalable and cost-effective means for widespread behavior change interventions (De Santis et al., 2022, p. 2; Müller et al., 2018).

In the context of PA promotion, smartphone applications (apps) often feature automated tracking capabilities, enabling users to receive continuous feedback on their progress and make informed decisions about their behavior.

A meta-analytic review by Romeo et al. (2019) examining the effectiveness of PA apps in increasing objectively measured PA in adults identified behavioral feedback as the only BCT consistently present across the apps included in their review. Be that as it may, their meta-analysis revealed a positive but nonsignificant influence of app-based interventions on PA. Researchers Yerrakalva et al. (2019) reported similar findings in older adults. Together, both studies underscore the fact that simply enabling continuous access to tracked measures (i.e., “feedback”) may not be enough to elicit significant change in PA behavior.

1.3 Self-regulation requires enactment

This apparent lack of volitional efficacy could be attributed to the level of proactive engagement required by the process of self-regulation as a whole. That is, while some self-regulatory BCTs, such as behavioral feedback, may be passively received, most require individuals to actually do something (e.g., set goals, make a plan, etc.), a concept known as ‘BCT enactment’ (Hankonen, 2021; Bellg et al., 2004).

A growing body of evidence supports the crucial role of BCT enactment in promoting behavior change in PA. For example, a longitudinal qualitative study by Bean et al. (2020) exploring the perceived PA journey of prediabetic women over a year concluded that transitioning from reliance on interpersonal strategies (such as social support) to intrapersonal strategies (including goal-setting and self-monitoring) may have explained higher self-reported levels of PA among participants (p. 709).

Quantitative studies further reinforce this notion. Hankonen et al. (2015) found a positive association between the number of BCTs enacted and self-reported PA in individuals with recently diagnosed diabetes, while Knittle et al. (2016) observed that greater use of self-regulatory BCTs partially explained the maintenance of PA in patients with rheumatoid arthritis six months post-intervention.

Moreover, the significance of enactment in fostering behavior change extends to digital PA interventions. A meta-analysis by Mclaughlin et al. (2021) investigating the relationship between engagement with digital health interventions and PA revealed a positive association between the two. For this, the analysis utilized various metrics to gauge engagement, including activities completed, logins, and time spent using the intervention. Interestingly, while activities completed and logins consistently correlated with PA, time spent using a digital intervention exhibited inconsistent associations with PA.

These findings support Hankonen's (2021) assertions regarding the importance of enactment, as the metrics of ‘activities completed’ and ‘logins’ offer a representation of active engagement that aligns closely with Bellg et al.'s (2004) definition of enactment. Whereas 'time spent using a digital intervention' lacks the active characteristic of enactment, thus exhibiting less consistent associations with PA outcomes.

1.4 Prompts to enhance enactment

Given the pivotal roles that enactment and self-regulation play in driving behavior change, it is crucial to direct individuals toward enacting the key components of self-regulation to achieve sustainable outcomes.

One potentially effective method for accomplishing this is through the use of prompts, which are defined as "environmental or social stimuli introduced with the purpose of prompting or cueing a target behavior" (Michie et al., 2013). Within the context of mobile health apps, prompts refer to any web- or mobile phone-based communication where individuals receive a written "notification" (e.g., text messages or push notifications) on their device's home screen without needing to take action first (MacPherson et al., 2022, pp. 3–4).

As previously discussed, Scheier and Carver's model of behavioral self-regulation (1988) outlines a continuous loop wherein individuals compare their behavior against a predefined goal, assess their progress, and direct their efforts toward minimizing discrepancies. Hence, central to this process are goals, feedback, and self-awareness (pp. 308–309), which respectively provide individuals with reference points, insights regarding their progress, and enable them to introspect on their behaviors in light of their goals.

Existing research confirms the efficacy of prompts in bolstering PA and self-regulatory self-awareness. For example, MacPherson et al. (2019) investigated the impact of mobile health prompts on at-risk adults enrolled in a year-long diabetes prevention program. They found significant increases in both self-monitoring and self-reported exercise in the three days following prompt delivery compared to the preceding three days. Particularly noteworthy was the even more pronounced effect observed on self-reported exercise during the initial six months of the trial, with significant increases noted in the three, five, and seven days following the delivery of a prompt compared to the respective days preceding the prompt.

Likewise, a meta-analysis by Smith et al. (2020) found that one-way text message interventions resulted in significantly higher objectively measured postintervention steps per day when contrasted with control groups that did not receive text messages.

Despite this growing body of research supporting the efficacy of mobile phone prompts in promoting PA, their potential to increase goal-setting frequency, a crucial aspect of behavioral self-regulation (Scheier et al., 2012), remains largely overlooked. Recent studies, exemplified by Zhou et al. (2018), highlights the importance of goals in driving PA behavior.

Zhou et al. (2018) compared the effectiveness of personalized daily step goals against fixed goals in university students over 10 weeks, revealing a notable increase in daily step count among those with personalized goals. Specifically, participants with personalized goals experienced an increase of 700 steps over the 10-week period, while those with fixed goals saw a concerning decrease of 1520 steps, resulting in a notable total difference of 2220 daily steps between the two groups.

Considering these factors, the study at hand aimed to, first, fill the research gap regarding the effects of smartphone notifications on goal-setting behavior. Second, extend its inquiry to explore the influence of smartphone notifications on PA behavior, building upon prior research investigating the role of prompts in enhancing PA. Finally, and secondary to the two main foci, examine the association between the different notification types and goal achievement.

Through this exploration, the study sought to enhance the understanding of how prompts influence self-regulation and its outcomes within the context of PA. To the best of our knowledge, this study represents the first direct examination of the impact of smartphone notifications on goal setting as an outcome.

2 METHODS

2.1 Objectives

The present study constitutes the second N-of-1 trial using the Precious app (Nurmi et al., 2020, 2023). The study aimed to assess the effects of two types of smartphone notifications: one prompting PA goal setting, and the other providing feedback on goal progress and achievement. The study hypothesized that these intervention components would significantly influence participants' daily steps, probabilities of goal setting, and goal achievement.

2.2 Participants

2.2.1 Recruitment

Participants were recruited from the general population of Helsinki, Finland, through commercial advertisements in a local newspaper and targeted ads on Facebook. Those who expressed interest in participating were contacted by the research team via email or phone to assess their eligibility for the study.

2.2.2 Inclusion criteria

Participant eligibility was determined based on the following criteria: adult volunteers aged 18 years or older who were able to speak Finnish and had a working understanding of English to engage with the content in the Precious app. Additionally, participants had to fall below the WHO's PA recommendation of 150 minutes of moderate-intensity PA per week (World Health Organization, 2010) and have no contraindications to PA. They also needed to own a smartphone compatible with the Precious app (iOS version 8 or higher; Android version 4.1 'Jelly Bean' or higher), and be willing to install said app on their smartphone, as well as wear an activity tracker for the duration of the study.

2.2.3 Exclusion criteria

To minimize possible confounding effects, individuals who had used activity trackers, health behavior change apps, or had participated in other behavior change trials or programs within six months of the trial were excluded from participating in the study. Additionally, individuals attempting to enroll concurrently with a friend or relative were deemed ineligible to avoid revealing the mismatched timing of the intervention conditions through the other participant's smartphone.

2.2.4 Sample size

Initially, the target sample size was set at 15 participants; however, due to technical issues with the app's server, recruitment was halted early on, resulting in a final sample size of six participants. This final sample included participants of both sexes, with ages ranging from 18 to 65 years. For a more detailed description of the recruitment process, please refer to Nurmi et al. (2023).

2.3 Materials

2.3.1 Precious app

The study's interventions were delivered via a modified version of the Precious app (Nurmi et al., 2020). Broadly speaking, the Precious app is a smartphone application designed to target reflective and spontaneous psychological processes and then study their impact on behavior.

In this trial, the Precious app served three main purposes: hosting self-regulatory elements for participants to engage with, delivering PA-related notifications, and collecting the participants' behavioral outcomes.

2.3.2 Activity trackers

To track daily steps, participants wore Xiaomi Mi Band activity bracelets throughout the study. These activity bracelets boast a step-count accuracy of 96.6% (El-Amrawy & Nounou, 2015) and have an estimated battery life of 40 to 50 days without charging (Nurmi et al., 2023).

2.4 Outcomes

The study assessed three main outcomes: daily steps, goal-setting behavior, and goal achievement. Daily steps were continuously monitored using the activity bracelets, which were programmed to timestamp and transmit the step counts to the corresponding participant's app every 10 minutes via Bluetooth (Nurmi et al., 2023). Conversely, participants' goal-setting behavior and goal achievement were tracked exclusively by the Precious app.

2.5 Intake procedure

Upon acceptance into the study, participants attended in-person intake sessions where they reviewed the study information sheet, which was previously sent to them via email, and provided their informed consent.

After reviewing the information and signing their informed consent forms, participants randomly selected an opaque envelope from a bag. Each envelope contained a study code to be entered into the Precious app, activating a unique intervention delivery sequence. Researchers assisted participants in installing the Precious app on their smartphones and entering their unique study codes.

Additionally, participants received the following items: a Mi Band activity bracelet, a Firstbeat Bodyguard 2 device for conducting a Firstbeat lifestyle assessment over two days before and after the trial (provided as a participation bonus), comprehensive instructions for all materials, and the researcher's contact details. Participants were instructed to follow the instructions until their follow-up meeting and were encouraged to contact the researchers for technical support.

It is important to note that although participants were informed of the PA-promoting features of the Precious app, they were never explicitly instructed to engage in PA.

2.6 Study design

The study employed a within-person (n-of-1) randomized controlled trial design, using 2-day periods as the unit of randomization. Every two days, the app randomized the participants into one of four conditions:

Condition A served as the study's control. During this condition, participants did not receive any notifications, yet maintained complete access to all the components of the app. Only the notifications were intentionally excluded.

Condition B prompted goal setting and action planning. During this condition, participants who had not confirmed their step goal for that day would be issued a notification at 9 a.m., prompting them to establish a step goal. Furthermore, participants who had not set an action plan (i.e., selected a specific activity to achieve their step goal, and a corresponding time to perform said activity) would receive a separate notification at 10 a.m., prompting them to set one.

Condition C encouraged PA through behavioral feedback. During condition C, participants who had confirmed their step goal for that day would receive a progress update notification at 4 p.m.; for instance: "You've taken [step total] steps so far today – that's [percentage amount] of your goal. Keep going!".

Alternatively, if a participant had not confirmed their step goal for that day, the 4 p.m. notification would instead relay a tally of steps taken up to that point and would encourage the participant to remain physically active; for example, "You've taken [step total] steps so far. Keep going!".

Lastly, condition D combined the features and notifications of conditions B and C. During condition D, participants received notifications prompting them to set step goals and action plans and also received behavioral and progress updates intended to encourage them to remain physically active.

Each 2-day unit was followed by a 'washout' day to allow the effects of the previous intervention to dissipate before the next one. Condition A was the only exception to the standard 2-day setup, lasting only one day instead of two. This adjustment was done in anticipation of the interventions' limited strength to induce lasting behavioral changes. Consequently, to avoid a potential four-day 'washout' period and ensure the continuity of the study, condition A was intentionally programmed to last only one day.

To ensure a balanced distribution of conditions within each participant, conditions were block randomized using a block size of eight (four conditions, each repeated twice). This procedure was performed twice for each participant, resulting in a total of 44 trial days (see Figure 1).

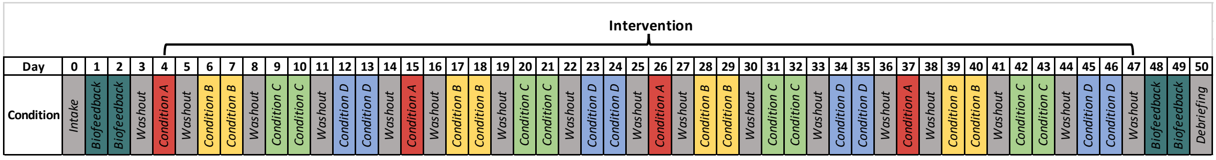

FIGURE 1. Intervention timeline example. Conditions B, C, and D last two days; condition A lasts one.

2.6.1 Randomization procedure

As referenced in the section describing the intake procedure, the process of randomization was done using computer-generated codes, which were printed and sealed individually in opaque envelopes. Each code corresponded to a unique intervention delivery sequence. During their intake meeting, each participant selected an envelope at random, opened it, and entered the code into the app. This activated their unique trial intervention sequence.

2.6.2 Components of the Precious app

Alongside notifications, the Precious app hosted an array of tools, which are comprehensively described in Nurmi et al. (2020). However, in this trial, the most important component (besides the notifications) was the ‘Mountain Climber’ tool. Here, participants engaged in goal-setting and action-planning by establishing their daily step goals and planning bouts of PA, including specifying activity type, intensity, and time of the day, to help them achieve these goals.

2.6.3 Precautionary measures

Similar to the first trial (Nurmi et al., 2023), the objective of this second trial was to evaluate the impact of intervention elements that required active cognitive engagement. Consequently, complete participant blinding to the intervention elements was not feasible.

Despite this limitation, several measures were implemented to mitigate participant awareness of the study’s objectives. Firstly, despite the prevalence of PA-related features in the study, participants were never explicitly instructed to engage in PA, nor were they informed of the study's hypotheses.

Secondly, participants were intentionally kept unaware of the sequences in which the intervention components were delivered via the Precious app. This is why candidates seeking to enroll alongside friends or relatives were deliberately excluded from the study; to avoid inadvertent exposure to the mismatched timing of the intervention conditions through the other participant's smartphone.

Lastly, the BCTs embedded within the various components of the Precious app were discreetly labeled using names such as 'Mountain climber', subtly diverting attention from the specific psychological processes being targeted.

Nevertheless, the effectiveness of these blinding measures was never formally tested.

2.7 Data analysis

The method of analysis chosen for this study was guided by the interest in examining the within-person effects of the app's notifications while accounting for intra-individual correlations due to repeated measures (Hoffman & Stawski, 2009, p. 98). Accordingly, multilevel modeling was selected for its robustness in handling temporal dependencies and grouping effects typical in longitudinal N-of-1 studies (Walls et al., 2006; Kwasnicka et al., 2019).

Through the implementation of within-person random effects, which allow both intercepts and slopes to vary within participants, multilevel models acknowledge the nuanced nature of individual behavior (Walls et al., 2006, p. 33). The variation in intercepts reflects differences in the starting points and propensities of the individuals before the introduction of intervention components (notifications), while the variation in slopes captures the individual differences in the responses to the same intervention component (Cushing et al., 2014, p. 144).

Allowing these components to vary freely enables researchers to capture the rich range of baseline behaviors and responses to different treatments or interventions, thus offering a nuanced understanding of within-person effects and providing personalized insights into their effectiveness (Walls et al., 2006, p. 33; Hoffman & Stawski, 2009, p. 98).

Examinations concerning binary outcomes—goal-setting behavior and goal achievement—were analyzed using a mixed-effects logistic regression, a subset of multilevel modeling. This approach estimates the log-odds of the outcomes—the likelihood of an event occurring relative to it not occurring—and then transforms these into probabilities on a scale of ‘0’ to ‘1’ (Sommet & Morselli, 2017). This conversion enhances the interpretability of the results by making the statistical output more intuitive and straightforward (Bewick et al., 2005).

In contrast, the analysis of continuous outcomes—daily steps—employed a linear mixed-effects model. Unlike mixed-effects logistic regressions, which are tailored for binary outcomes, linear mixed-effects models are equipped to analyze a wider range of outcomes, including continuous variables like step counts (Brauer & Curtin, 2018).

Moreover, in addition to accommodating inter-individual variability, linear mixed-effects models are effective at handling intra-individual skewness arising from factors within the individual, such as fluctuations in PA over time, as well as potential outliers (e.g., Batschelett et al., 2023, p. 1324). That is because, unlike traditional models, which often rely on assumptions of normality, linear mixed-effects models can capture the distributional characteristics of continuous data without having to rely on such assumptions (Arnau et al., 2012).

All models were fitted using the 'lme4' package in R, treating instances of missing data as missing completely at random and employing full information maximum likelihood estimation. Random effects of both types of notifications were applied at the within-person level, allowing parameters to vary randomly between participants and modeling all possible random effects (Finch et al., 2016). Additionally, all reported confidence intervals (CIs) were calculated using a 95% confidence level, which is consistent with the standards set by the American Psychological Association (2010).

2.8 Ethics

This study received ethical approval from the University of Helsinki Ethical Review Board in the Humanities and Social and Behavioral Sciences (statement 3/2016).

3 RESULTS

3.1 Missing Data

Instances of missing data, indicated by days where the registered step count was zero, were attributed to some participants occasionally removing their activity bracelets before going to sleep and forgetting to put them back on the next day. These instances were treated as 'missing completely at random.' Consequently, accompanying data from days with no step counts were excluded from the analysis (Lüdtke et al., 2017, p. 150).

This decision was made on the basis that these occurrences were considered infrequent technical issues, not prevalent across all participants, and deemed unrelated to any of the characteristics or conditions of the study. As such, it was assumed that the resulting missingness in the data was independent of both observed and unobserved factors (Rubin, 1976; Lüdtke et al., 2017).

Additionally, the implementation of multilevel modeling's built-in mechanism of full information maximum likelihood estimation provides a robust framework for handling missing data by using all available data to estimate model parameters without the need to exclude participants with incomplete data, ultimately enhancing the power and efficiency of the analysis (Walls et al., 2006, p. 11).

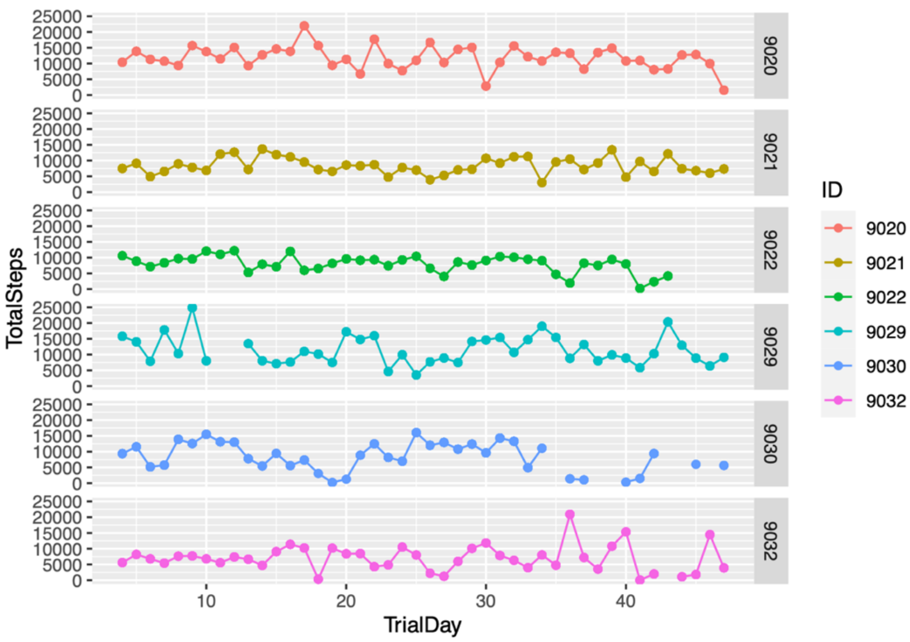

FIGURE 2. Plot of daily steps showcasing days of missing data across time. Examples of missing data points are evident between days 10 and 13 for Participant 9029, and between days 34 and 40 for Participant 9030.

3.2 Effects of goal-setting and action-planning notifications on goal-setting behavior

TABLE 1: Probabilities of goal-setting, with and without goal-setting and action-planning notifications. 95% confidence intervals.

	Goal Prompt Off			Goal Prompt On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	0.006	0.038	0.197	0.186	0.691	0.956
9021	0.011	0.051	0.211	0.774	0.954	0.992
9022	0.005	0.036	0.207	0.072	0.52	0.938
9029	0.001	0.012	0.185	0.371	0.926	0.996
9030	0.037	0.116	0.308	0.04	0.278	0.78
9032	0.001	0.013	0.183	0.466	0.941	0.997

The results of the mixed-effects logistic regression reveal a low baseline level of goal-setting behavior across participants, as evidenced by the intercepts, reflecting a generally low inclination toward setting goals in the absence of goal-setting and action-planning prompts.

The introduction of goal-setting and action-planning prompts resulted in a notable increase in goal-setting behavior across the cohort, as evidenced by the coefficients, which quantify the impact of these prompts on goal-setting behavior. However, the variation in the range of the estimated effects of the prompts between participants indicates that the degree and consistency of this influence differed across the sample.

For participants 9020, 9022, and 9030, the confidence intervals of the prompt effect overlapped with their respective baseline confidence intervals (see Figure 3), which suggests that the presence of goal-setting and action-planning prompts did not result in a statistically distinguishable increase in the goal-setting behavior of these participants compared to their baseline levels.

For participants 9029 and 9032, the CI of the prompt effect crossed the threshold probability of 0.5, encompassing a range of probabilities above and below 50%. This crossing suggests that while the prompts might have occasionally enhanced their probability of goal-setting above chance, the inclusion of values below this threshold within the same CI indicates significant variability.

Thus, although there were moments when the prompts appeared effective, they did not consistently produce a clear, statistically significant effect beyond the baseline levels, leading to uncertainty about the reliability of these prompts in consistently enhancing goal-setting behavior in these participants.

Finally, and in stark contrast with all other participants, participant 9021 was the only participant who exhibited a clear and consistent positive response to the prompts, indicating a statistically significant increase in the likelihood of setting a goal when prompted using goal-setting and action-planning prompts.

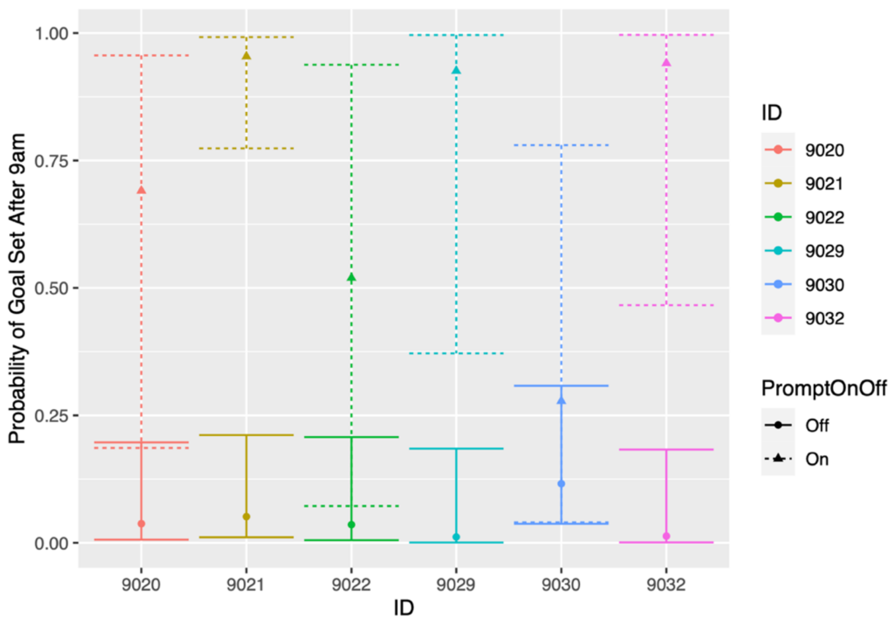

FIGURE 3. Effects of goal-setting and action-planning prompts on goal-setting behavior vary across participants. Participant 9021 showed a consistent, statistically significant increase. Participants 9029 and 9032 experienced inconsistent effects, with probabilities sometimes above but not reliably different from the baseline.

3.3 Effects of goal-setting and action-planning notifications on daily steps

TABLE 2: Summary statistics of daily steps.

	Daily Steps					
ID	Minimum	Q1	Median	Mean	Q3	Maximum
9020	1545	9972.5	11389	11828.818	14024.25	21942
9021	3027	6856.75	7807.5	8370.568	9904.75	13656
9022	228	6985.5	8491.5	7984.375	9562.75	12195
9029	3532	8019.75	10229	11441.762	14713.75	24889
9030	225	5478.25	9113	8398.789	12461	16042
9032	51	4509.5	6783	7013.093	8765.5	20921

The exploratory analysis of daily step counts revealed considerable variations among participants throughout the trial. For example, Participant 9020 recorded the highest average daily step count at 11,829 steps per day, while Participant 9032 recorded the lowest at 7,013 steps per day. Additionally, Participants 9020, 9029, and 9032 exhibited maximum daily steps that nearly doubled their respective averages, suggesting sporadic periods of intense PA. In contrast, Participants 9021, 9022, and 9030 exhibited maximum step counts that were proportionally closer to their daily averages, indicating a more consistent level of PA throughout the trial.

TABLE 3: Estimated daily steps with and without goal-setting and action-planning notifications. 95% confidence intervals.

	Goal Prompt Off			Goal Prompt On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	10764.492	11889.327	13014.163	-295.824	-270.255	-244.686
9021	7288.413	8413.249	9538.084	-216.809	-191.24	-165.672
9022	6837.437	8016.589	9195.741	-209.027	-182.224	-155.421
9029	10331.952	11482.986	12634.02	-287.182	-261.018	-234.854
9030	7222.565	8432.726	9642.887	-219.191	-191.683	-164.175
9032	5903.076	7041.086	8179.095	-185.918	-160.05	-134.182

The results of the linear mixed-effects model reveal substantial differences in the participants' baseline step counts, with figures ranging between 5,903 and 13,014 steps per day before the presence of goal-setting and action-planning prompts.

Upon the introduction of goal-setting and action-planning prompts, the model identified a generalized decrease in daily steps across the cohort. The extent of this effect varied, albeit marginally, between participants, with decreases in step counts ranging from 134 to approximately 296 steps on the days when goal-setting and action-planning prompts were present.

Despite this, the fact that the CIs of the prompt effect are fully within those of the intercepts for all participants (see Figure 4) suggests that the reductions are not statistically significant as they fall within each participant's expected range of natural variability in step counts. This implies that the practical influence of goal-setting and action-planning prompts on daily steps may not have been significantly different from the participants' usual fluctuations in step counts.

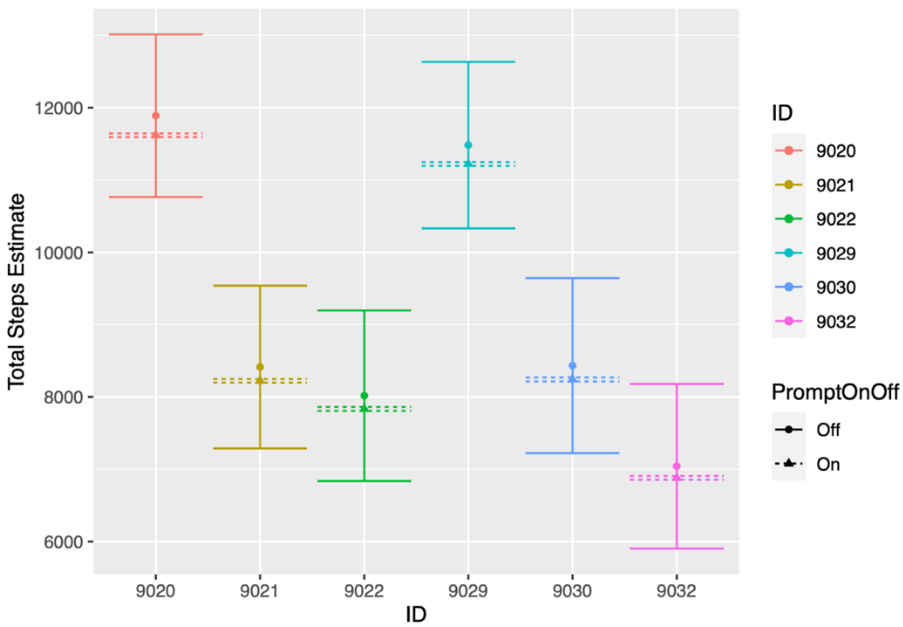

FIGURE 4. No discernible alteration in daily step counts despite goal-setting and action-planning notifications.

3.4 Effects of goal-setting and action-planning notifications on goal achievement

TABLE 4: Probabilities of goal achievement, with and without goal-setting and action-planning notifications. 95% confidence intervals.

	Goal Prompt Off			Goal Prompt On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	0.349	0.481	0.615	0.281	0.539	0.777
9021	0.407	0.535	0.658	0.212	0.431	0.68
9022	0.373	0.51	0.646	0.23	0.479	0.74
9029	0.364	0.5	0.636	0.247	0.5	0.753
9030	0.349	0.481	0.615	0.281	0.539	0.777
9032	0.349	0.481	0.615	0.281	0.539	0.777

Unlike the previous two analyses, the baseline probabilities of goal achievement, represented by the intercepts, remained relatively consistent across participants, ranging from approximately 0.35 to 0.66. This suggests a broad yet realistic likelihood of goal achievement among participants before the introduction of goal-setting and action-planning prompts.

Upon the introduction of goal-setting and action-planning prompts, the probabilities of goal achievement, depicted by the coefficients, displayed even greater variability across all participants.

However, the presence of the threshold probability of 0.5 within the prompt-related CIs, coupled with the complete overlap of the baseline CIs, across all participants, suggests that the effects of these prompts on goal achievement are not statistically distinguishable from the baseline in this dataset, as the CIs of the intercept are fully encompassed by those of the coefficient (see Figure 5).

Nonetheless, the amplified variability in the probabilities of goal achievement in response to goal-setting and action-planning prompts may signify the potential influence of unaccounted variables mediating the effect of prompts on goal achievement.

One key observation contributing to this variability is the dependence of goal achievement on goal setting; without a set goal, achievement was not possible. There were only 25 instances where goal setting took place, which led to an equally limited number of instances where goal achievement was possible. Of those, only 17 coincided with days when goal-setting and action-planning prompts were active. Examining the distribution of these instances among participants dilutes the dataset even more. Participant 9021 exhibited the highest number of potential goal achievement instances on prompt days, with nine. Participant 9032 had four, while Participants 9020 and 9029 had two instances each, and Participants 9022 and 9030 had none.

In summary, the limited number of observations prevents a definite conclusion regarding the impact of goal-setting and action-planning prompts on goal achievement.

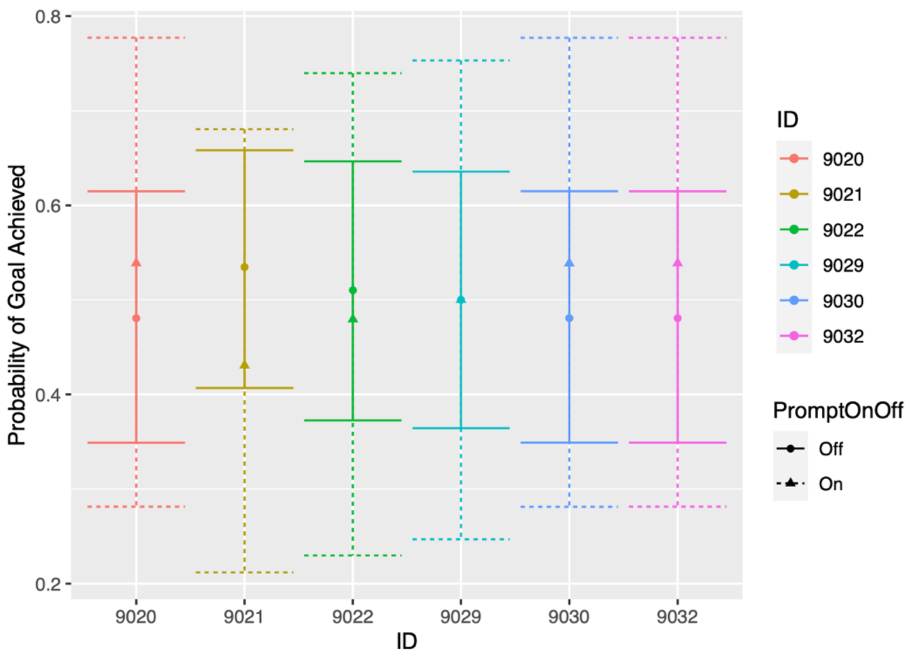

FIGURE 5. Complete overlap of confidence intervals indicates no discernible effect of goal-setting and action-planning prompts on goal achievement across all participants.

3.5 Effects of behavioral feedback notifications on goal-setting behavior

TABLE 5: Probabilities of goal setting, with and without behavioral feedback notifications. 95% confidence intervals.

	Feedback Off			Feedback On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	0.002	0.023	0.188	0.177	0.692	0.959
9021	0.0	0.0	0.573	0.177	0.984	1.0
9022	0.0	0.0	0.626	0.165	0.983	1.0
9029	0.0	0.0	0.599	0.171	0.984	1.0

9030	0.0	0.004	0.221	0.342	0.946	0.998
9032	0.0	0.007	0.176	0.44	0.946	0.997

The results of the mixed-effects logistic regression reveal that in the absence of feedback notifications, participants generally exhibited a very low baseline probability of setting step goals—with the lower bounds of the intercept CIs approaching zero in most cases.

The introduction of feedback notifications prompted an increase in goal-setting behavior; however, the magnitude and consistency of this effect varied notably among participants, a finding similar to that of the first analysis, where the impact of goal-setting and action-planning prompts on goal-setting behavior varied among participants.

In this case, the CIs for the effect of the feedback notifications on goal-setting probabilities for participants 9020, 9021, 9022, and 9029, overlapped with their baseline CIs. This indicates that the presence of feedback notifications did not significantly enhance goal-setting probabilities beyond their usual baseline.

In contrast, for participants 9030, and 9032, the effects of feedback notifications were more pronounced, with their CIs not overlapping with baseline values and spanning across the threshold probability of 0.5 (see Figure 6). This suggests a stronger, albeit inconsistent, influence on goal-setting behavior. The crossing of the 0.5 threshold suggests that while feedback notifications effectively enhanced goal-setting at times, the variability within these intervals reflects some inconsistency, and calls for cautious interpretation and further investigation.

In that regard, it is important to acknowledge the potential influence of data scarcity on this outcome. Among the 25 instances of goal-setting throughout the study, merely three occurred after 4 p.m. on days when feedback notifications were present. Consequently, only these instances could reasonably be linked to the presence of feedback notifications.

Particularly interesting is the fact that all three instances of goal setting post-4 p.m. were observed within participants 9032 and 9030, who also displayed distinct coefficient CIs compared to their baselines. This observation hints at a potential association between feedback notifications and goal setting after 4 p.m. However, further data is needed to corroborate or refute this trend conclusively.

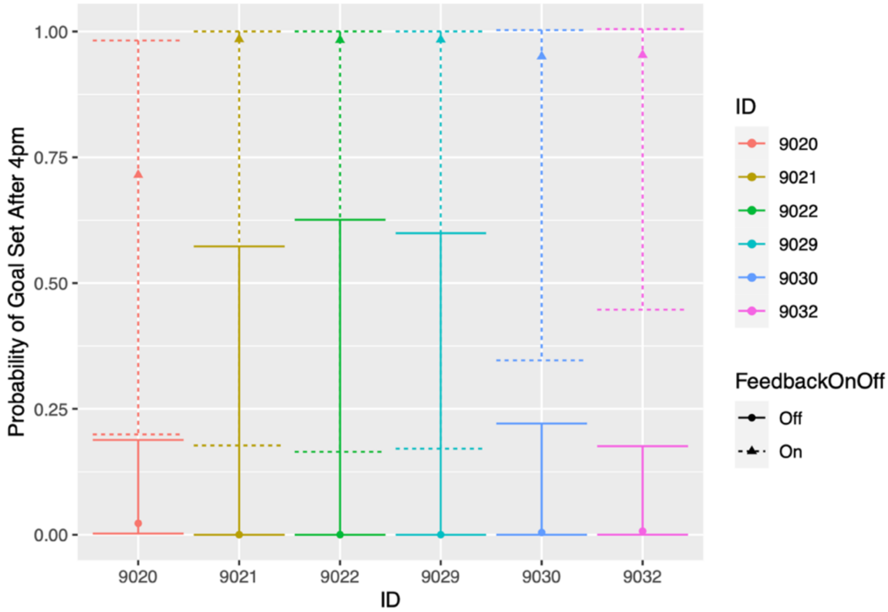

FIGURE 6. Varying effects of behavioral feedback notifications on goal-setting behavior. Participants 9030 and 9032 exhibited increases in goal-setting behavior. However, the crossing of the 0.5 threshold suggests inconsistency in the effectiveness of the notification.

3.6 Effects of behavioral feedback notifications on daily steps

TABLE 6: Estimated daily steps with and without behavioral feedback notifications. 95% confidence intervals.

	Feedback Off			Feedback On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	10698.684	11818.046	12937.407	-108.021	-98.675	-89.329
9021	7246.032	8365.393	9484.755	-79.193	-69.847	-60.501
9022	6802.028	7975.672	9149.316	-76.392	-66.593	-56.794
9029	10287.401	11432.94	12578.479	-105.024	-95.459	-85.895
9030	7183.451	8387.112	9590.773	-80.078	-70.028	-59.978
9032	5872.447	7004.561	8136.674	-67.937	-58.485	-49.032

The results of the linear mixed-effects model revealed substantial differences in the participants' baseline step counts, with figures ranging between 5,872 and 12,937 steps per day before the presence of feedback notifications.

Similar to the effects of goal-setting and action-planning prompts on daily steps, the presence of feedback notifications was also associated with a decrease in daily steps across the cohort. The extent of this effect varied marginally between participants, with decreases ranging between 49 and 108 steps per day (see Table 6).

Furthermore, the fact that the CIs of the coefficient are fully within those of the intercepts for all participants (see Figure 7) suggests that these reductions in daily steps are not statistically significant as they fall within each participant's expected range of natural variability in step counts. This implies that the practical influence of feedback notifications on daily steps was not statistically different from the participants' usual fluctuations in step counts.

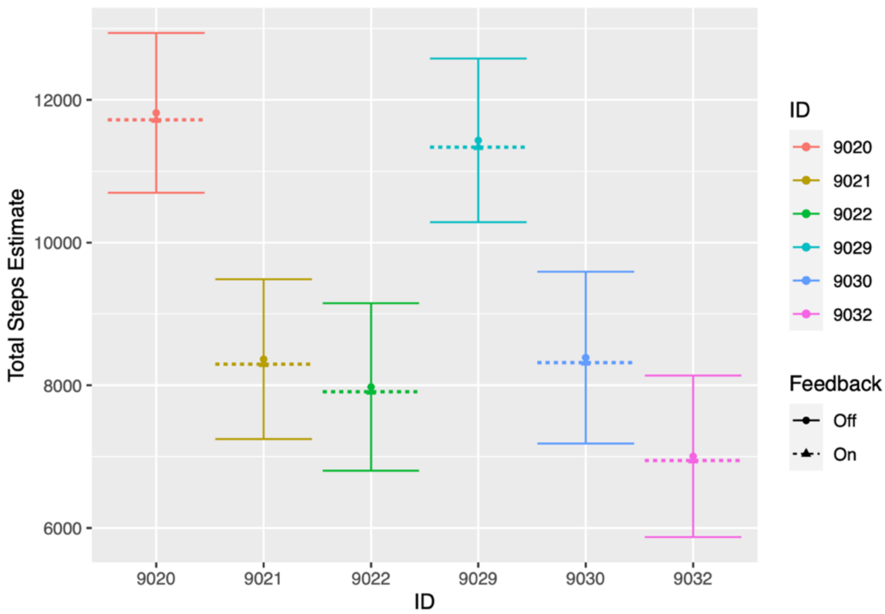

FIGURE 7. No discernible alterations in daily step counts in response to behavioral feedback notifications.

3.7 Effects of behavioral feedback notifications on goal achievement

TABLE 7: Probabilities of goal achievement, with and without behavioral feedback notifications. 95% confidence intervals.

	Feedback Off			Feedback On		
ID	Lower CI	Estimate	Upper CI	Lower CI	Estimate	Upper CI
9020	0.5	0.5	0.5	0.5	0.5	0.5
9021	0.5	0.5	0.5	0.5	0.5	0.5
9022	0.5	0.5	0.5	0.5	0.5	0.5
9029	0.5	0.5	0.5	0.5	0.5	0.5
9030	0.5	0.5	0.5	0.5	0.5	0.5
9032	0.5	0.5	0.5	0.5	0.5	0.5

The probabilities of goal achievement remained consistent across conditions for all participants. The mixed-effects logistic regression revealed no discernable difference in goal achievement probabilities between days when feedback notifications were active and when they were inactive. Both the estimated effects of the feedback notifications and the baseline probabilities were centered at 0.5, with no variation in the CIs, suggesting that feedback notifications did not influence goal achievement in this study.

This lack of effect could be partly attributed to data scarcity. As previously noted, goal achievement was contingent on goal setting; without established goals, achievement was implausible. Only 25 instances of goal setting were recorded in the entire trial. Of these, merely 14 coincided with feedback notifications, and only three could potentially be attributed to them as they occurred after 4 p.m. Ultimately, only two of these instances resulted in goal achievement.

To summarize, the entire model tried to predict the probabilities of goal achievement based on three instances of goal setting and two instances of goal achievement. This scarcity of goal-setting and goal-achievement instances within feedback notification days might have severely constrained the model's power to detect any effect.

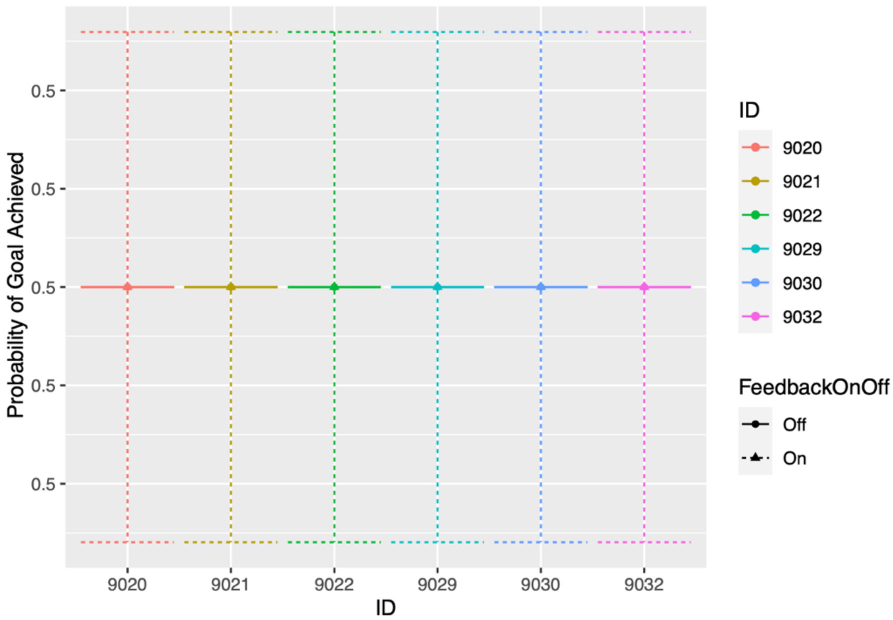

FIGURE 8. Probabilities goal achievement for each participant, with similar outcomes both with and without behavioral feedback notifications.

4 DISCUSSION

4.1 Effects of goal-setting and action-planning notifications on goal-setting behavior

The primary finding of this study was the significant efficacy of goal-setting notifications in consistently influencing the goal-setting behavior of one participant out of the six enrolled. For two other participants, the effects of the notifications were statistically noticeable but inconsistent, showing efficacy only occasionally and not across all instances. This variability in effectiveness suggests individual differences that warrant further investigation.

Future studies could benefit from integrating qualitative methods alongside quantitative analyses to provide deeper insights into the observed efficacy of goal-setting notifications in specific individuals (e.g., Cauchard et al., 2019).

4.2 Effects of behavioral feedback notifications on goal-setting behavior

Feedback notifications exhibited a statistical difference from the baseline goal-setting behavior in two participants, indicating a potential influence on goal-setting behavior; however, the effect was not consistently reliable.

A significant caveat in this analysis was the low incidence of goal-setting after 4 p.m. on days when feedback notifications were present; only three instances were recorded across the sample. Two possible explanations for this are worth considering:

Firstly, the text displayed with the feedback notification did not prompt participants to use the tap action feature embedded in the notification. Instead, as the name implies, the text merely provided behavioral feedback; "You've taken [step total] steps so far today. Keep going!". In contrast, the text displayed with the goal-setting notification prompted participants to use the tap action feature embedded in the notification; "Tap here to set your step goal for today" or "What's the plan? Tap here to add to your plan for today".

Secondly, the timing of the notification could have been an important factor. Feedback notifications were dispensed at 4 p.m., whereas goal-setting notifications were dispensed at 9 a.m. Setting a goal later in the day, when self-regulatory resources may be diminished, could be less probable (Hagger et al., 2010).

Future studies examining these variables could benefit from larger samples to enhance the reliability of the results. Earlier dispense times for feedback notifications should also be considered.

Finally, exploring alterations to the tap action feature of the notification to prevent preemptively guiding participants toward goal setting is warranted. During this study, the tap action feature of the feedback notification directed participants to the 'Mountain Climber' tile (the goal-setting and action-planning component of the app), potentially leading to biased instances of goal-setting in response to feedback notifications. Redirecting participants to a different tile in the app, such as a summary of their step count, might offer a more organic opportunity to observe whether participants naturally respond to behavioral feedback notifications by setting a goal.

4.3 Effects of goal-setting and action-planning notifications on daily step counts

In contrast to their impact on goal-setting behavior, goal-setting notifications did not affect daily step counts, aligning with Polgreen et al.'s (2018) finding of no significant differences in step counts between participants receiving morning text reminders to set step goals and those in other groups.

However, Polgreen et al. (2018) did observe a significant increase in steps on days when participants set step goals, emphasizing the importance of enacting goal-setting in PA interventions, as individuals appear to achieve higher levels of PA when actively setting goals compared to when they do not.

Hence, future studies should investigate whether a correlation exists between days when step goals are established and subsequent increases in step counts. Such investigations could provide further evidence of the importance of incorporating, and potentially prioritizing, goal-setting in PA interventions.

4.4 Effects of behavioral feedback notifications on daily step counts

Similarly, behavioral feedback notifications demonstrated no significant impact on daily step counts. This outcome is consistent with prior research findings where behavioral feedback notifications failed to influence daily step counts, despite variations in modalities and frequencies (Conroy et al., 2023; Cauchard et al., 2019; Whelan et al., 2019). This consistent lack of impact reinforces Hankonen's (2021) assertion that behavior change necessitates BCT enactment. Behavioral feedback ('Feedback on behavior'; Michie et al., 2013), by itself, is not enactable.

For example, Conroy et al. (2023) compared the efficacy of self-monitoring and feedback prompts on participant's daily step counts, revealing that only self-monitoring prompts were positively associated with increased daily step counts. This demonstrates the superiority of self-monitoring above behavioral feedback in enhancing daily step counts, implying that behavioral feedback may need additional action to effectively induce behavior change.

A promising avenue for future research lies in pairing behavioral feedback with other BCTs and evaluating their combined effects on daily step counts compared to behavioral feedback alone. Such investigations could offer valuable insights into optimizing digital PA interventions, which currently rely heavily on behavioral feedback (Romeo et al., 2019).

4.5 Effects of goal-setting, action-planning, and behavioral feedback notifications on goal achievement

Finally, neither goal-setting nor feedback notifications demonstrated any effect on participants' goal achievement. The widening of the CIs of the coefficient across the sample during the examination of the relationship between goal-setting notifications and goal achievement suggests two plausible explanations.

Firstly, wider CIs for the coefficient compared to those for the intercept indicate increased uncertainty in estimating the intervention's effect. This uncertainty could stem from variability in participant responses due to individual differences, or the presence of unaccounted factors, such as important predictors or covariates influencing the relationship. If critical variables that affect goal achievement are missing from the model, the estimated effects of the intervention can reflect higher uncertainty.

In this case, the relationships between the notifications and goal achievement were mediated by goal setting. Thus, a mediation analysis would have been appropriate. However, and this is the second likely explanation for the widening of the CIs of the coefficient, the scarcity of instances of goal setting and goal achievement presents a major challenge for a meaningful mediation analysis. With only 25 instances of goal setting and 13 instances of goal achievement among six participants, the estimated effects are likely to remain highly uncertain and unstable, even with a proper mediation analysis.

As a result, it is reasonable to say that the true influence of goal-setting and feedback notifications on goal achievement remains elusive in this study and warrants future investigations using larger samples.

4.6 Strengths and weaknesses

The biggest strength of this study was its N-of-1 design, where all participants were exposed to every condition multiple times throughout the trial, providing valuable insights into the nuanced effects of each notification. The variation in participants' responses underscores the critical notion that not all individuals respond to intervention components the same way, highlighting the importance of understanding individual differences in behavioral interventions.

Equally, the study's main limitation was its small sample size. Technical problems with the app's server led to an early halt in recruitment, resulting in a final working sample of six participants instead of the initially intended 15. Future studies should aim to replicate these findings across larger samples to enhance the reliability and applicability of the results.

Another area for improvement is the use of two different devices for step counting and data collection. Specifically, the connectivity between two devices may introduce vulnerabilities to data reliability. During the initial stages of statistical analysis, the research team discovered irregular and unexplained drops in some participants' total daily step counts. This could be attributed to the dependency on Bluetooth connectivity between the activity bracelet and the participant's smartphone for transmitting step counts to the app.

The intermittent loss of connectivity could have led to instances where the total daily step count reset to the most recent transmission between the activity bracelet and the app, multiple times throughout the day. While this issue was addressed by manually adding step counts before analysis, the reliance on two separate devices poses risks to data reliability. Modern smartphones are equipped with built-in sensors such as accelerometers and gyroscopes, making them increasingly accurate and self-reliant for step data collection (Wu et al., 2012). As a result, future studies should consider utilizing smartphones as the primary tool for data collection to mitigate these reliability concerns.

5 CONCLUSION

This study represents the second N-of-1 trial utilizing the Precious app. Its primary objectives were to evaluate the impact of two types of smartphone notifications on participants' goal-setting behavior, daily step counts, and goal achievement. One notification type prompted goal-setting and action-planning, while the other provided behavioral feedback on goal progress and achievement.

The study's contributions to the field are as follows:

- This study is the first, to our knowledge, to examine the effects of goal-setting smartphone notifications on goal-setting behavior. The results show that goal-setting notifications enhance the probability of setting goals among some individuals.
- Similarly, this study is the first, to our knowledge, to examine the effects of feedback smartphone notifications on goal-setting behavior. The results show that feedback notifications have the potential to enhance the probability of goal-setting among some individuals. However, this finding warrants caution due to the size of the data.
- Additionally, the findings of this study align with existing literature demonstrating that neither goal-setting nor feedback notifications significantly impact daily step counts.

Overall, these findings suggest that while the use of goal-setting and behavioral feedback notifications may enhance goal-setting behavior in some individuals, their overall impact on physical activity may be limited. Larger samples, minor adjustments to the feedback notifications used in this trial, and additional analyses could help improve the robustness and generalizability of these findings.

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