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Design and evaluation of a just-in-time adaptive intervention to promote physical activity in obese individuals

Master thesis

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Abstract

Background: Obesity is a pressing public health concern due to its rising prevalence and association with a range of physical and mental conditions. Increasing physical activity (PA) is a commonly used strategy in both prevention and treatment of obesity. The combined lifestyle intervention (CLI) aims to promote sustainable behavior change in several domains, including PA. However, the CLI requires intensive coaching, which impedes large-scale implementation. mHealth is identified as a potential approach to support this. A promising mHealth intervention design is the just-in-time adaptive intervention (JITAI), which aims to provide the right digital behavior change support at the right time. An example of this is the provision of prompting users to be active. However, systematic design and inclusion of behavioral theory and behavior change techniques (BCTs) is often limited in current JITAIs. Furthermore, the optimal frequency and timing of providing activity prompts to mHealth users is not yet clear.

Aim: To systematically design and evaluate a JITAI to promote PA behaviors in obese individuals.

Methods: The systematic design will be guided by two established frameworks, which ensures the application of behavioral theory and BCTs in the intervention. A set of 91 tailored activity prompts were written in accordance with the process of writing tailored health messages proposed by Kreuter. The JITAI was designed in accordance with the components proposed by Nahum-Shani. A fourteen-day micro randomized trial (MRT) among 13 participants was conducted to investigate the optimal timing and frequency of activity prompts to promote PA behaviors.

Results: An increased daily step count was observed when participants received 1 activity prompt compared to receiving no activity prompt ($p < 0,001$). No statistically significant difference in daily step count was observed when participants received 2 prompts compared to receiving no activity prompt ($p = 0,24$). When receiving 1 activity prompt, an increased daily step count was observed when this prompt was received in the morning compared to when the prompt was received in the evening ($p < 0,001$). No difference was observed when the prompt was received in the morning compared to when the prompt was received in the afternoon ($p = 0,19$). No significant differences in step counts were observed among the various combinations of dayparts when participants received two prompts.

Discussion: The MRT conducted in the second stage of the report revealed that the implementation of activity prompts can effectively enhance daily step count among obese individuals. The findings indicate that sending a single activity prompt in the morning yields the most pronounced impact on promoting PA behaviors compared to the absence of activity prompts. However, these findings should be interpreted cautiously as study duration and sample size were limited. Follow-up research is needed to draw more robust conclusions on the effectiveness and to further develop the JITAI.

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Introduction

Being overweight or obese has been identified as one of the leading risk factors for global mortality, accounting for more than 5 million deaths annually (1). Obesity has become a pressing public health concern due to its rising prevalence, which has nearly doubled over the past four decades and is not expected to stop in the short term (2,3). In 2021, about 14 percent of the Dutch population was estimated to be obese (4). Moreover, according to a recent study, the societal cost of an overweight or obese individual in the Netherlands is nearly €11,500 per year (5). Obese individuals are at elevated risk of morbidity associated with a range of physical conditions, such as type 2 diabetes, coronary heart disease, and certain types of cancers (6). In addition, obesity is associated with the development of various psychological conditions, including depression and stress (7). Given the health risks and economic burden associated with obesity, it can be argued that the government should prioritize both prevention and treatment efforts.

Increasing physical activity (PA) is a commonly used strategy in both prevention (8) and treatment (9) of obesity. A relatively novel strategy to increase PA in obese individuals is the combined lifestyle intervention (CLI), which the Dutch government reimburses as of 2019. Besides promoting PA behaviors, the CLI aims to promote sustainable behavior change in the domains diet, sleep, stress, and relaxation. This type of intervention consists of 2 phases: [1] an intensive treatment phase and [2] a maintenance phase. During the treatment phase, participants receive intensive coaching from a certified lifestyle coach to learn about optimizing nutrition, PA behaviors, and forming healthy habits. This includes both individual and group coaching sessions. During the maintenance phase, coaching is less intensive as participants are expected to become more self-sufficient in those behaviors. Research has shown that the CLI is effective in improving PA behaviors and weight loss in the short term (10,11). Conversely, weight loss interventions, such as the CLI, often lack long-term effectiveness, as weight regain is common (12,13). Therefore, ongoing coaching during the maintenance phase may be imperative to maintain PA behaviors and consequently sustain weight loss. However, ongoing in-person coaching may present a challenge for large-scale implementation due to the high associated costs (14). Thus, the development of supportive approaches for coaching delivery may be necessary to overcome these challenges and maintain weight loss through improving PA behaviors.

Hence, several studies (15,16) have identified mobile health (mHealth) interventions as a potential approach to promoting a healthy lifestyle, as these technologies are considered scalable and cost-effective (17). mHealth interventions have been shown to improve various health behaviors such as PA (17–20), weight management (21), and dietary habits (22). Moreover, personalized (i.e., tailored) mHealth interventions, are shown to be more effective than generic interventions in promoting health behaviors (23). By providing information that is specifically relevant to each individual user, these interventions are more likely to have a substantial impact (24). Literature has demonstrated that tailoring enhances the persuasiveness of interventions (25), which subsequently leads to increased adherence (26). Increased adherence to mHealth interventions is in turn associated with higher intervention effectiveness (27). Additionally, users consider tailored mHealth interventions more valuable for promoting PA behaviors than generic interventions (28). Commonly used tailoring approaches in mHealth include displaying personal PA data, tailored text messages, and providing personalized feedback (29). However, research also points out that there is a need for more sophisticated tailoring approaches, such as adopting behavioral theory in intervention development, since this is not common practice currently (30,31). Additionally, current interventions often use static tailoring (e.g., based on a single assessment) instead of dynamic tailoring (e.g., based on repeated assessments). Dynamic tailoring is a more refined approach and had been shown to be more effective than static tailoring in behavior change interventions (32). This includes delivering an appropriate type of behavior change support when the user is most in need and receptive to it (33).

A promising intervention design to provide the right support at the right time is the just-in-time adaptive intervention (JITAI) (34). A JITAI is commonly defined as: "*an intervention designed to address the dynamically changing needs of individuals via the provision of the type/amount of support needed, at the right time*" (35). The development of sensing technologies (e.g., wearables, GPS) enables frequent measurement of the individuals' conditions and environmental context, allowing for versatile personalized support (36). This could involve sending prompts (e.g., push notifications) to mHealth users aimed at improving PA behaviors when they didn't reach their daily step goal yet. For example, Ding et al. (37) found that sending prompts at anticipated opportune moments encourages users to engage in PA more compared to sending prompts at random times. Opportune moments included instances of prolonged sedentary time or smartphone usage, as well as when users were already engaged in walking. However, the authors did not assess the participants' objective PA levels but solely inquired whether the system motivated them to engage in more physical activity. Therefore, it is not clear if the participants were indeed more active after receiving a prompt. In another study, Rabbi et al. (38) found promising results in sending personalized activity suggestions automatically. Their results indicated that contextually tailored activity suggestions were more effective than generic activity suggestions in improving PA behaviors.

Despite the great potential that JITAIs hold for behavior change, the research in this domain is still in its early stages. For instance, many interventions lack behavior-theoretical substantiation (39), while including theory in the development process is associated with higher effectiveness in interventions for improving PA (40,41). Therefore, Hardeman et al. (42) recommend including appropriate behavioral theory and behavior change techniques (BCTs) when developing JITAIs (43). A BCT is defined as: "*an observable, replicable, and irreducible component of an intervention designed to alter or redirect causal processes that regulate behavior; that is, a technique is proposed to be an active ingredient*" (44). Furthermore, social cognitive theory (SCT) (45) and the health action process approach (HAPA) (46) are examples of behavioral theories and have been shown to predict health behaviors. Therefore, these could be included in the design process of an intervention (47–49). Those theories address factors that in turn can be influenced by appropriate BCTs.

Another key challenge in the development of a JITAI is determining how to deliver activity prompts, as the optimal frequency and timing of sending activity prompts in not yet clear (50–53). Moreover, too frequently delivered prompts might lead to user disengagement (54,55) and habituation (e.g., decreased responsiveness from repeated exposure to stimuli) (56). Hence, intervention delivery should be limited to the minimal effective dose. Furthermore, current interventions are often described inadequately. Therefore, researchers urge to use design principles to guide the systematic development process of a JITAI (42). Finally, the utilization of commonly used experimental designs (e.g., randomized controlled trials (RCTs)) may not provide sufficient support for the development of JITAIs, as they do not enable researchers to determine the specific timing for delivery of intervention components and the extent to which a just-in-time intervention has achieved its intended effect (36). RCTs are designed to assess whether an entire intervention influences the outcome behavior. However, in JITAI development, researchers aim to investigate the time-varying (e.g., when to send a prompt) effects and how this is influenced by the context in which the prompt is sent. Thus, there is a need for study designs that support JITAI development through evaluation of both the optimal timing and causal effects of the intervention (57).

A novel research design to guide the development of JITAIs is the micro-randomized trial (MRT), as proposed by Klasnja et al. (58). This is a technique that involves random allocation of an intervention to a participant at every relevant decision point. The decision points are identified based on theoretical considerations, the individual's past behavior, and their current context. An MRT can provide valuable insights in the development of a JITAI as each intervention component can be randomized multiple times for each participant. For instance, a participant can be randomized each day to either receive no activity prompts or to receive activity prompts. This allows for within-person assessment of the effectiveness of activity prompts on daily step count, as each participant serves as their own control. Additionally, the effects on the group level can also be investigated by comparing the effects on step count between participant days when no prompts were sent and days when prompts were sent. To date, only a limited number of MRTs have been conducted, primarily with the purpose of evaluating and developing JITAIs targeting the promotion of physical activity (59–61) and increase of mHealth engagement (62). An MRT can provide valuable insights into the delivery of a JITAI for each mHealth user by investigating the optimal number and timing of prompts to be sent.

Aim of the study

Currently, there exists a research gap in both the systematic design of a JITAI and how the intervention should be delivered to maximize effectiveness (43). Therefore, the aim of this study is twofold. First, to systematically design a JITAI to promote PA in obese individuals participating in a CLI based on existing frameworks, using appropriate behavioral theory and BCTs. To optimize the JITAI, an MRT will be conducted to assess how the delivery of the intervention affects an individual's PA behaviors, which is a necessary first step in developing a personalized coaching system. The MRT aims to evaluate the optimal number of daily prompts to send and the optimal timing for their delivery to determine the most effective coaching approach.

Ancora Health

The JITAI will function as an automated tailored coaching system to improve PA for participants of the CLI offered by Ancora Health. Ancora Health offers a 2-year technology-supported CLI program. That is, participants receive both online coaching and can use an mHealth application that guides the behavior change process. It employs both individual and group online coaching. The first six months consist of an intensive coaching phase. Participants in this phase receive weekly online group coaching sessions and monthly online individual coaching sessions. The group coaching sessions enable participants to discuss, among other things, the barriers and facilitators for their behavior change. This allows participants to motivate and learn from each other. Furthermore, participants can chat with their coach through the application. This phase is followed by a 1.5-year maintenance phase, in which participants try to maintain their behavior change and continue to lose weight. In this phase, coaching is less intensive (i.e., 4 individual and 2 group coaching sessions). However, the application aims to support the participants by employing multiple features. For instance, it offers tools to track progress, and to acquire and maintain healthier lifestyle habits for weight loss. These tools will be further elaborated later in the report.

Report structure

The report is divided into 2 stages: a description of [1] the systematic design of the intervention based on an existing framework, appropriate behavioral theory, and corresponding BCTs, and [2] the MRT for evaluating the developed intervention. In addition, the final section of the report provides a general discussion that synthesizes the findings of the study and compares those to similar research, outlines the strengths and limitations of the current study, and offers insights on the implications for future research.

Stage 1: Design

Method

Several aspects need to be considered in the intervention design process to maximize its effectiveness. To structure this process, the program planning model as described by Kreuter was adopted (63). This framework aims to establish a systematic approach in intervention design by first analyzing the (health) problem and subsequently identifying appropriate behavior change theory to influence this. The information derived from the analysis was then translated into a program framework. According to Kreuter, developing a program framework involves: "*identifying appropriate communication strategies to effectively address the health issue, and translating these strategies into specific program activities*" (63). The JITAI development framework of Nahum-Shani et al. (57) describes several components to develop appropriate communication strategies and to convert these into program activities. Hence, the step "developing a program framework" was guided by the JITAI development framework, with the framework components detailed in the method section of this step.

Figure 1 depicts the systematic intervention development. The original program-planning model from Kreuter was slightly adjusted. That is, the order of some steps was changed, and some steps were merged. Furthermore, the model was supplemented with the JITAI development components of Nahum-Shani. First, the health problem was analyzed. Second, a program framework was developed. In this step, both frameworks were combined. The steps developing tailoring assessments, creating tailoring algorithms, and automating the tailoring process were considered part of developing a program framework. As the JITAI component tailoring variables corresponded with the process step developing tailoring assessments, these steps were merged. The same applies to the JITAI component decision rules, which corresponded to the process steps creating tailoring algorithms and automating the tailoring process. Additionally, the JITAI components decision points and intervention options were added to developing the program framework as these are crucial in JITAI development (57). Third, tailored health messages were written. Fourth, the program was implemented in the Ancora Health application. Fifth, an MRT was conducted to evaluate the program.
Table 1 provides a brief description of the employed process steps. This section will present a concise summary of the employed process steps and methods of intervention development. A more detailed overview of the results of the development and characteristics of the intervention will be provided in the Results section.

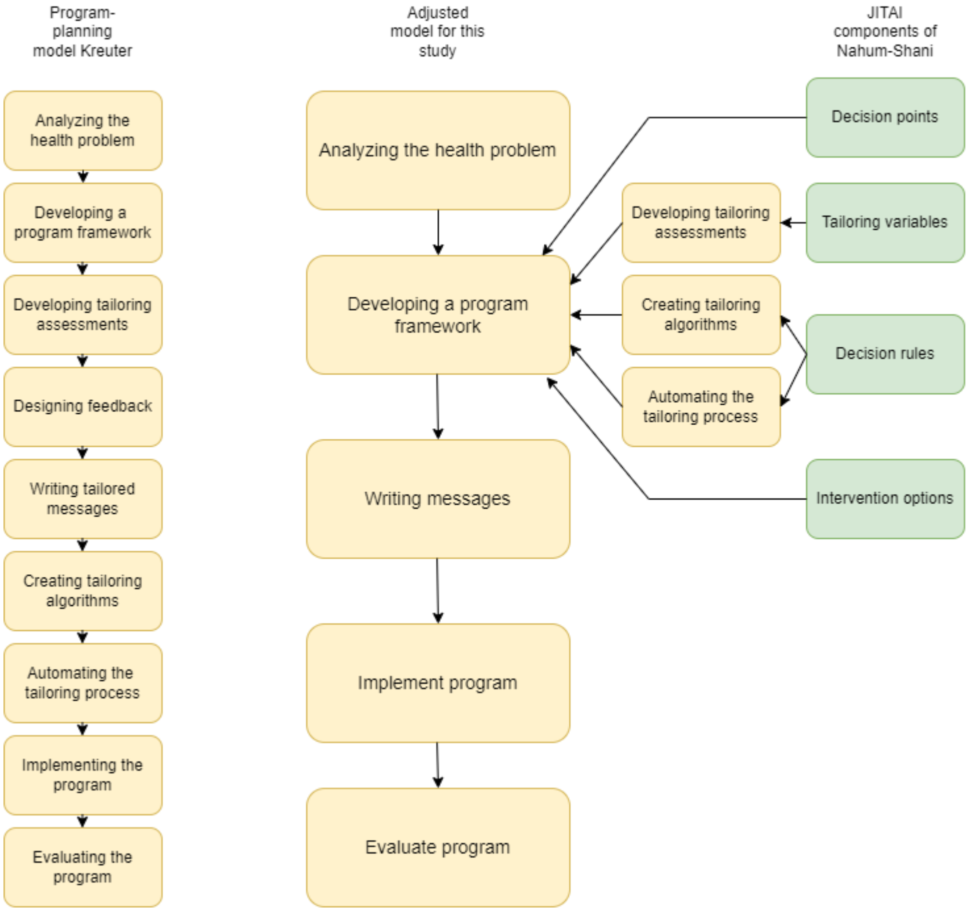

Figure 1. Original program-planning model of Kreuter (63) *(yellow elements) and the adjusted model used for this study including components of Nahum-Shani* (57) *(green elements).*

Table 1. Process of systematic design and evaluation of the intervention.

Steps	**Description**
Step 1: Analyzing the health problem	- Describe behavioral theory and determinants that predict PA behaviors - Identify BCTs that influence these determinants
Step 2: Program framework development[a]	- Develop intervention (JITAI) based on components described by Nahum-Shani et al. (57)
Step 3: Writing messages[b]	- Create a set of messages that include identified BCTs
Step 4: Implement program	- Implement intervention in Ancora Health application
Step 5: Evaluate program	- Conduct MRT to evaluate the intervention

[a]*This step combines developing tailoring assessments, creating tailoring algorithms, automating the tailoring process of Kreuter* (63)*, and the JITAI components of Nahum-Shani* (57).
[b]*This step combines writing tailored messages and designing feedback of Kreuter* (63)

Target population

The intervention targeted obese individuals aged 18 or older that were participating in the technology-supported CLI of Ancora Health at the time of the study.

Analyzing the health problem

Behavioral theory and determinants

To identify behavioral determinants linked to physical activity, a behavioral theory that can explain PA behaviors was selected first. For the identification of a suitable behavioral theory, expert consultation was sought from the first supervisor of this report. Based on their guidance, the HAPA model was recommended for the intervention. To validate this choice, a literature search was conducted to examine previous interventions utilizing the HAPA model to increase PA behaviors. Additionally, the model was augmented with supplementary determinants that have been shown to influence health behavior change. The model that was constructed is elaborated on in greater detail in the Results section.

BCTs

Based on the identified behavioral determinants, a literature search was performed to identify specific BCTs that could effectively target and modify these determinants. The search yielded various sources, including the Theory and Techniques tool, which provided insights into BCTs that have been shown to influence the identified determinants (46,64–67). Furthermore, during the selection process of BCTs, consideration was given to their practical application within the coaching messages. BCTs that were not deemed relevant or suitable for inclusion in the intervention were omitted from the final selection. The details of the selected BCTs will be elaborated upon in the Results section.

Program framework development

The intervention development process and creation of tailoring assessments and algorithms were guided by the framework proposed by Nahum-Shani et al. (57). This framework consists of 6 elements: [1] decision points, [2] tailoring variables, [3] intervention options, [4] decision rules, [5] proximal outcomes, and [6] distal outcomes. Decision points are points in time where a decision (e.g., delivery of the intervention) must be made. A tailoring variable refers to individual-specific information that is used to determine which intervention should be offered at a decision point (35). For instance, a tailoring variable can be the accumulated daily step count. Intervention options refer to the array of possible types of support at a particular decision point (57). These could include motivational messages, feedback, or advice. Decision rules link the intervention options and tailoring variables in a systematic way (57). Table 3 provides some examples of decision rules. Proximal outcomes are the short-term goals the intervention options are intended to achieve, such as daily step count. Distal outcomes are the ultimate goal the intervention aims to achieve, for instance increased PA behaviors. Figure 2 illustrates a conceptual model of the JITAI components. The application of the elements in the intervention will be outlined in the Results section.

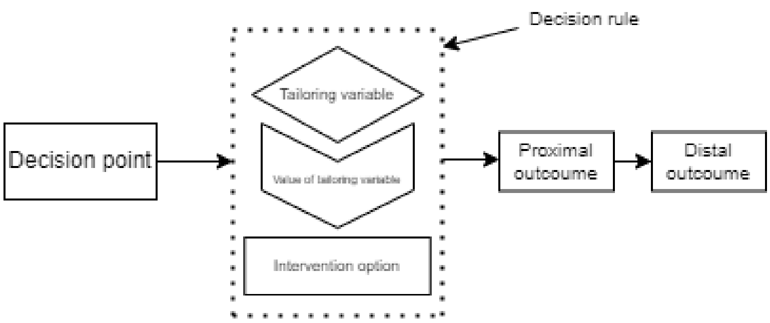

Figure 2. Conceptual model of a JITAI

Writing messages

A set of messages was written which included the identified BCTs that promote PA behaviors (i.e., daily step count). As mentioned previously, persuasiveness of the technology is important for increasing adherence to it, which subsequently increases the effectiveness of the intervention. Additionally, including behavioral theory is associated with higher intervention effectiveness (40). Therefore, both the self-determination theory (SDT) (68) and Persuasive Systems Design (PSD) (25) elements were explored to include in the messages to enhance intrinsic motivation and persuasiveness of the messages. Furthermore, the created messages were based on the tailoring assessments which resulted from the program framework. For instance, a morning specific message often contained morning-specific information (e.g., Good morning, <name>!). Following the initial development of the coaching messages, a review was undertaken by the Ancora Health intervention development team, who subsequently provided feedback. The feedback was then incorporated into the messaging content, with the aim of increasing and improving the messaging content.

Implement program

After developing the framework and writing the messages, the intervention was implemented in the Ancora Health application. This is a mHealth technology focused on lifestyle improvement and offers a range of health and care programs, including a technology-supported CLI. It leverages technology so scaling up the CLI supply is facilitated, as it requires less intensive personal coaching. To obtain this, it employs several strategies which will be discussed in the Results section.

Evaluate program

The evaluation of the developed intervention is described in stage 2 of the report and will therefore not be discussed in more detail in the design process.

Results

Analyzing the health problem

Behavioral theory and determinants

The HAPA is a theoretical framework that aims to explain behavior change and has effectively been employed in previous interventions targeting PA behavior (46,48,49,69). It is categorized as a stage model, which assumes that different interventions are appropriate at different stages (or phases) of health behavior change. First, the distinction between a pre-intentional motivation phase (i.e., intention to change) and a post-intentional volition phase (i.e., execution of behavior change) is made. Moreover, it allows for tailoring the intervention to individual needs as the HAPA model suggests classifying individuals as either nonintenders, intenders, or actors. Individuals in the motivation phase are classified as nonintenders (i.e., no intention to change), whereas individuals in the volition phase can be labeled as intenders (i.e., intention to change) or actors (i.e., perform new behavior). Figure 3 illustrates a conceptual overview of the HAPA model.

Once the individuals are classified, the determinants that influence their behavior should be recognized. The HAPA model is built on the concept of self-regulation. Health self-regulation involves motivation, volition, and action, which enables individuals to abandon health-compromising behaviors in favor of adopting and maintaining health-enhancing behaviors (70). Thus, self-regulatory efforts of an individual can ensure health-compromising behavior is eliminated and health-enhancing behavior is adopted instead (46). This is consistent with a substantial body of research indicating that self-regulation plays a critical role in behavioral change, encompassing both the initiation and action phases (71–74). Thus, improving self-regulation skills is crucial in all phases of behavior change. Furthermore, multiple types of self-efficacy hold a pivotal position within the HAPA, returning in all phases of the model. The role of self-efficacy will be further specified below.

Additionally, the model describes phase-specific behavioral determinants. First, the HAPA suggests that risk perception, outcome expectancies, and task self-efficacy are predisposing factors for nonintenders (46). Risk perceptions are an individual's beliefs about potential harm and severity of a risk when maintaining the current behavior. Outcome expectancies refer to an individual's perceptions regarding potential gains and/or losses associated with performing a particular behavior, as well as their assessment of the likelihood that the behavior will result in a specific outcome. Task self-efficacy refers to the individual's beliefs concerning their ability to execute the new behavior (46).

Second, intenders need to bridge the gap between intention and action. The intention-behavior gap refers to the disparity between individuals' intentions to engage in a particular behavior and their actual behavior (75). To overcome this gap, action planning, coping planning, and coping self-efficacy processes should be improved (46). Action planning involves making specific plans for executing the health behavior. That is, individuals that make an action plan describe when, where, and how the behavior will be performed (76). Coping planning refers to identifying barriers and developing alternative behaviors to overcome them (77). For example, an if-then plan can be created: *"If I want to walk but the weather is bad, I will do a workout inside"*. Finally, coping self-efficacy refers to the beliefs an individual holds regarding their ability to cope with those barriers.

Third, actors should focus on maintaining their newly adopted behavior and preventing relapses. Marlatt and Gordon's relapse prevention model states that enhancing self-efficacy is crucial to be able to handle challenging situations without lapsing (78). Moreover, according to the HAPA model, the ability to prevent relapses involves improving recovery self-efficacy. Recovery self-efficacy is the confidence one has in their ability to resume progress towards their goal after experiencing setbacks or failures and to minimize any negative effects. It pertains to the individual's trust in their competence to regain control and reduce harm (79).

Additionally, the model was augmented with additional determinants that influence health behavior change. Specifically, positive social influences and habit formation are also considered vital elements for behavior maintenance by prior research (80). Hence, the determinants social influences and habits were considered important for individuals classified as actors and were therefore incorporated into the model. Habit formation is proposed to occur following a period of effective self-regulation of a novel behavior. As behaviors are consistently repeated over time, consciously controlled actions become automated and are hypothesized to be executed outside of conscious awareness (81). Therefore, once a habit is formed, individuals decrease their reliance on self-regulation processes, thereby reinforcing the newly adopted behavior.
Social influence refers to the occurrence when an individual's opinions, emotional states, and behaviors are affected by others (80). Individuals are more inclined to follow advice and guidance from people they perceive as trustworthy and with whom they have a sense of connection (82). Therefore, according to the SDT, to enhance intrinsic motivation to sustain a newly adopted behavior in the long term a sense of relatedness with others must be developed (68,83). Additionally, SDT states that targeting competence and autonomy are also crucial in maintaining intrinsic motivation for sustained behavior change.

The to-be-developed intervention will be tested on participants that followed the CLI-program for at least 16 weeks at the study start. Therefore, it was assumed that the participants already established an intention to change. Hence, participants were not classified as nonintenders, but were either classified as intenders or actors. The rationale behind the categorization of participants will be expounded upon in the section "Program framework development".

The specific model used for this study is depicted in Figure 3.

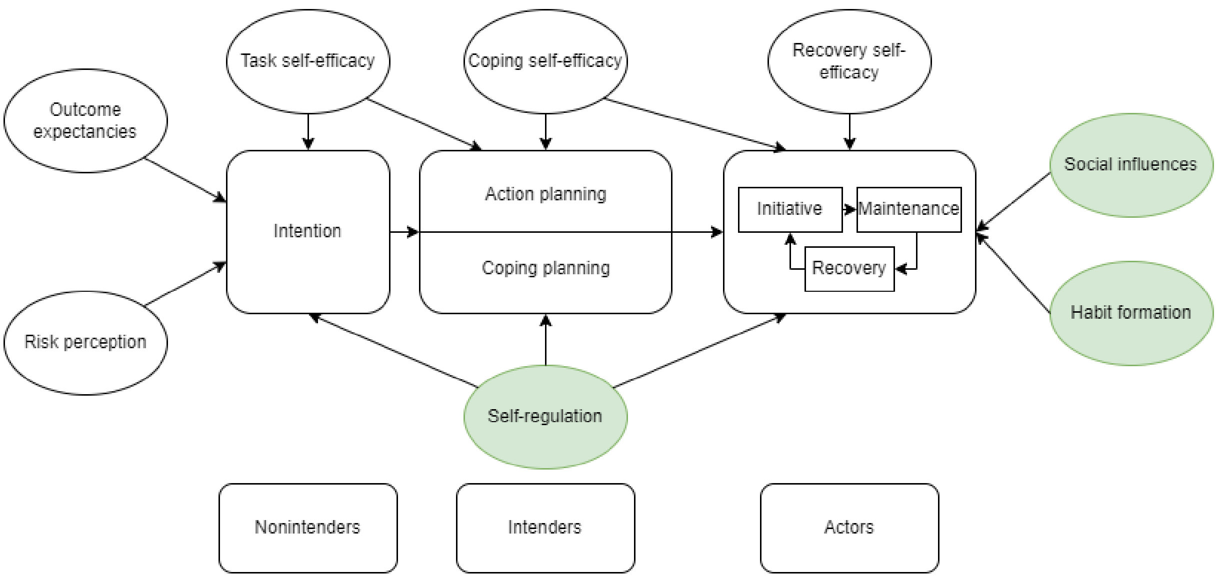

Figure 3. Augmented HAPA-model (46) *used for this study. Elements in green represent added determinants*

BCTs

The literature search resulted in multiple BCTs that influence the behavioral determinants. The BCTs were included in the written messages.

First, Michie et al. (41) discovered that interventions that incorporated the BCT self-monitoring of behavior with at least one other BCT that targeted self-regulation were more effective in promoting PA behaviors than interventions that did not include these BCTs. The other BCTs targeting self-regulation are goal setting, feedback on behavior, and review of behavioral goals (41). Additionally, the Theory and Techniques tool showed that the BCT reduce negative emotions improves self-regulation. Therefore, these BCTs were included in the intervention.

Second, appropriate BCTs that target self-efficacy were identified. Olander et al. (84) found that, among others, the BCTs action planning and social support were associated with improvements in self-efficacy. Another meta-analysis (66) confirmed this and additionally found that the BCT instruction on how to perform behavior was also associated with higher self-efficacy. Furthermore, the Theory and Techniques tool (65) showed that the following BCTs were associated with higher self-efficacy: goal setting of behavior, coping planning, graded tasks, verbal persuasion about capability, focus on past success, self-talk, and self-monitoring. Hence, those BCTs were included to target self-efficacy.

Third, according to the HAPA model (46), individuals who engage in both action planning and coping planning are more likely to achieve a change in their behavior. Therefore, those BCTs were also included in the intervention.

Fourth, relevant BCTs to help creating habits were identified. The Theory and Techniques tool showed that the BCTs habit formation and prompts/cues were effective in developing habitual behavior.

Fifth, BCTs that can affect the determinant social influences were identified. These included social support, social comparison, information on others approval, and social reward. Hence, these BCTs were also included in the intervention.

The results of the literature search are summarized in Table 2. The definitions of the identified BCTs can be found in the BCT taxonomy v1 (44).

Table 2. BCTs linked to behavioral determinants

		Determinants					
		Both phases		Intenders		Actors	
		Self-regulation (64)	*Self-efficacy* (65–67,84)	*Action planning* (46)	*Coping planning* (46)	*Habits* (65,80)	*Social influences* (65,80)
BCTs	*Goal setting*	X	X				
	Coping planning		X	X	X		
	Action planning		X	X	X		

	Instruction on how to perform behavior		X				
	Graded tasks		X				
	Reduce negative emotions	X					
	Verbal persuasion about capability		X				
	Focus on past success		X				
	Self-talk		X				
	Self-monitoring	X	X				
	Feedback on behavior	X					
	Review of behavioral goals	X					
	Social support		X				X
	Habit formation					X	
	Prompts/cues					X	
	Social comparison						X
	Information on others approval						X
	Social reward						X

Program framework development

The program planning model of Kreuter (63) states that in the intervention development, there needs to be a tailoring assessment and tailoring algorithms to provide the right treatment to an individual. The framework of Nahum-Shani et al. (57) supports this by providing a systematic approach to developing intervention components, including tailoring variables and decision rules. Those components will be outlined below.

Decision points

One of the key challenges in designing a JITAI is the identification of decision points. To date, the optimal frequency and timing of the intervention delivery remain unclear (85). Therefore, one of the objectives of the MRT will be to explore how to deliver the intervention for each participant to maximize effectiveness. So, the MRT will provide information on how many daily prompts should be sent and when sending prompts seems most effective. This serves as guidance for compiling appropriate decision points. The research design will be described in stage 2 of the report.

Tailoring variables

Initially, the JITAI will contain three tailoring variables. Step goal achievement was selected as the first tailoring variable. That is, an activity prompt was sent when a user did not reach their daily step goal yet. Conversely, feedback was provided when a user reached their daily step goal. This was monitored passively by extracting step data from a wearable or mobile phone. Second, the phase of change was selected as tailoring variable. If a participant's step goal decreased for two consecutive weeks, they were classified as intenders. Otherwise, they were categorized as actors. The adjustable step goal feature of the application was used to inform this decision. This feature is discussed in greater detail in the "Implement program" section. To reduce participant burden, categorization to the phase of change was also monitored passively. Third, time of the day was also selected as tailoring variable. For instance, when a message was sent between 8 am and 12 pm, it would contain morning-specific information (e.g., Good morning, <name>!). The same applies to messages sent in the afternoon and evening.

Intervention options
The first intervention option is a motivational message, delivered as a push notification. These messages are based on the identified behavioral determinants and include appropriate BCTs aimed at increasing PA levels. As outlined above, the motivational messages are tailored to the phase of change and time of day. Once participants have been categorized into their phase of change, they receive messages that include BCTs that have been shown to influence the relevant determinants for that particular phase. For instance, intenders receive messages aimed at improving action and coping planning processes. Conversely, actors receive messages targeted to habit formation and social influences. As self-regulation and self-efficacy are considered valuable for each phase, all participants can receive messages targeted at those determinants. Furthermore, the developed messages were specific for the time of the day, as described above. The second intervention option is a feedback message. These messages were identical for each participant and were sent whenever a participant reached their daily step goal at a particular decision point. Providing feedback on performance has been associated with greater PA intervention effectiveness (86). Finally, the last intervention option is to provide nothing. Including a "provide nothing" intervention option is an important strategy to minimize negative intervention effects such as intervention fatigue and decreased engagement (57). To determine which intervention option should be delivered, decision rules must first be established.

Decision rules
The decision rules contain the values of tailoring variables (e.g., step count), cut-off values (e.g., step goal), and intervention options (e.g., provide feedback). To cover all possible intervention options, a set of 3 decision rules was created. The links between the tailoring variables, decision rules, and intervention options are presented in Table 3. Additionally, some examples of messages are displayed in the table.

Table 3. Links between tailoring variables, decision rules, and intervention options.

Tailoring variable	**Decision rule**	**Intervention option**	**Example**
Step goal achievement	IF step count < daily step goal THEN motivational message ELSE IF step count ≥ daily step goal AND no feedback has been provided yet THEN positive feedback ELSE provide nothing	Motivational message, feedback message	Feedback message when step goal is achieved: Title: Today's step goal Body: Well done <name>! You've reached your step goal for today!

Phase of change	IF step goal decreased for 2 consecutive weeks THEN intender message ELSE actor message	Motivational message	Intender phase, morning-specific message: Title: Making an exercise plan Body: Good morning <name>! Try to make your plan to be active as specific as possible. Think about when, where, and how you will do this!
Time of day	IF time ≥8 AM and time ≤12 PM THEN (morning-specific message) ELSE IF time >12 PM and time ≤5 PM THEN (afternoon-specific message) ELSE IF time >5 PM and time ≤8 PM THEN (evening-specific message)	Motivational message	Actor phase, evening-specific message: Title: Today's step goal Body: Good evening <name>! How many steps have you taken today? Maybe you can still reach your goal tonight!

A schematic overview of the decision rules is presented in Figure 4.

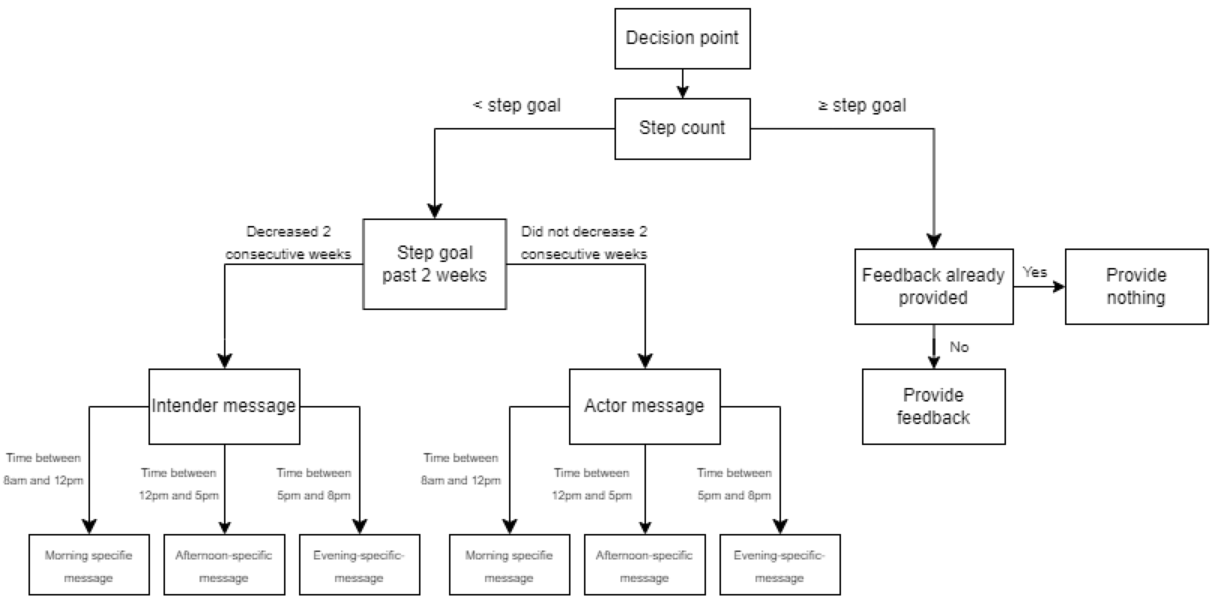

Figure 4. Decision rules

Outcomes
The primary objective of the JITAI is to enhance PA levels among individuals with obesity, which can also be denoted as the distal outcome. The number of daily steps is considered the proximal outcome of this JITAI. Attaining the proximal outcomes or short-term goals of the

JITAI can lead to the achievement of the distal outcome. That is, consistently reaching a high daily step count can lead to overall enhanced PA levels.

Writing messages

To ensure a sufficient level of diversity in the messages, a collection of 91 messages was compiled into a library.
The messages aimed to motivate and advise people to improve or maintain PA behaviors. The messages were written in both Dutch and English up to a maximum B1 level to ensure that the content was comprehensible to each participant. The messages consisted of both a title and a body. The title contained the general theme of the message, such as: *"Making an exercise plan"*. The body contained more detailed information, such as: *"Make your plan concrete by deciding when, where, and how you will exercise. This increases your chances of success!"*. The title and body were respectively limited to 34 and 138 characters, including spaces. As mentioned previously, the messages were tailored to phase of change and time of the day. For instance, a morning-specific message for an intender could be: "*What are you going to do today to achieve your goal? It helps to describe for yourself what you want to do and for how long!*" The BCT action planning is considered the "active ingredient" of this message. An evening-specific message for an actor could be: *"If you have little energy in the evening to exercise, try to plan it at times when you normally feel more energetic."* The BCT employed in this message is coping planning.
Additionally, in accordance with SDT, the messages aimed at targeting autonomy, competence, and relatedness. Specifically, the messages were formulated in a moderately general manner to preserve participants' sense of autonomy, encouraging them to engage in physical activity without specifying a particular activity. Furthermore, to enhance participants' feelings of competence, certain messages provided compliments on their progress thus far. Relatedness was targeted by messages that encouraged individuals to involve friends or family members in walking or exercising together. Finally, the messages included several design principles derived from the PSD framework (25). First, personalization was used through addressing users by their first name. Second, the messages were tailored to the user, as described in the section "Tailoring variables". Third, some messages included the PSD principle praise by providing positive feedback when a user reached their goal. Fourth, some messages included suggestions through providing users information on how to be more active. The complete message collection can be found in Appendix A.

Implement program

The JITAI was integrated into the Ancora Health application. This section will provide a brief overview of the features the application comprises in addition to the reported intervention.

First, users of the application can self-monitor both their behavior and health data. This includes the objectively measured number of steps and resting heart rate. Additionally, this includes self-reported calorie intake, sleep duration, weight, and waist circumference. Second, the app incorporates an adaptive step goal-setting feature. When starting the intervention, users set a step goal together with their coach. When the goal is not met for 3 or less of the last 7 days, it will be reduced by 500 steps. When the goal is met for 4 of the last 7 days, it remains unchanged. When the goal is met for more than 5 of the last 7 days, it will increase by 500 steps. Third, the app contains lessons on various health-related themes. These include topics on PA, nutrition, mindfulness, as well as teaching specific health-related skills such as how to deal with relapses. Finally, the application incorporates a chat feature that allows users to chat with their coach. The developed JITAI will be integrated as the latest feature of the application and will function as an automated PA coaching system that delivers push notifications to the user. Several screenshots of the mobile application are depicted in Figure 5. An overview of the technology-supported CLI program is illustrated in Figure 6.

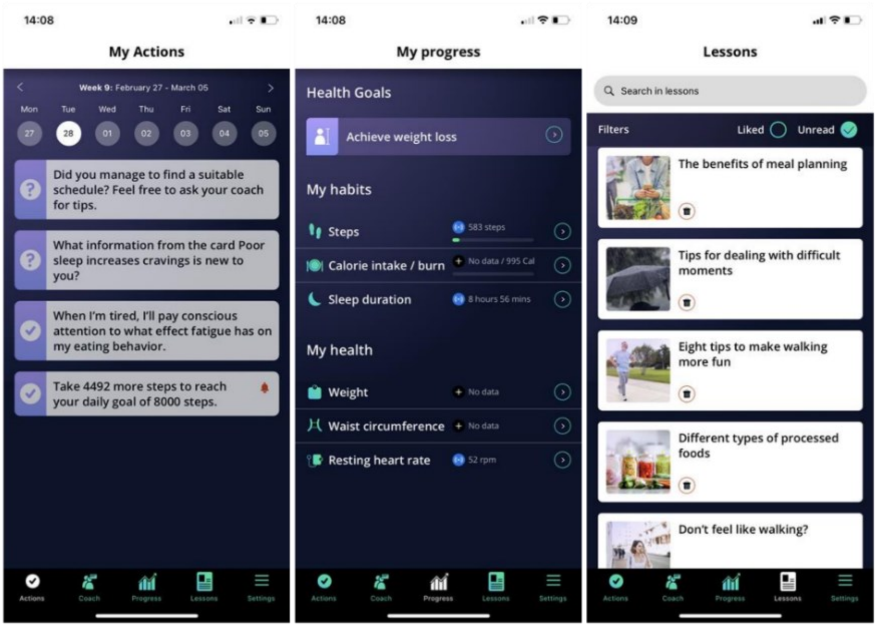

Figure 5. Screenshots of Ancora Health application

Figure 6. Overview CLI-program

Stage 2: Evaluation

Method

Study design

The JITAI was evaluated in a fourteen-day MRT study design. This study design aims to assess how activity prompts should be delivered by answering the following research questions:

- How does the daily dose of activity prompts affect the daily step count in obese individuals that participate in a CLI?
- How does the timing of activity prompts affect the daily step count in obese individuals that participate in a CLI?

It is hypothesized that sending two activity prompts per day will result in a higher daily step count compared to sending no activity prompts. Furthermore, it is hypothesized that sending one activity prompt per day will result in a higher daily step count compared to sending no activity prompts. Additionally, it is hypothesized that prompts delivered in the morning will have the strongest effect on daily step count, followed by afternoon prompts and then evening prompts. This hypothesis is based on the assumption that participants have a longer duration to notice and act upon a morning prompt throughout the day, whereas the window of opportunity for acting upon an evening prompt is shorter.

The study protocol was approved by the Computer & Information Sciences Ethics Committee of the University of Twente and was stored under application number 230217. Participants of the CLI offered by Ancora received an informed consent form at the start of the program. The form contained information about what happens with participants' data, as well as applicable laws and regulations regarding data protection (GDPR) to which Ancora adheres. The form also included a link to the full privacy policy of Ancora Health. The informed consent form can be found in Appendix D.

Procedure

Participants were instructed to track their steps during waking hours when they started the technology supported CLI program of Ancora Health. Each morning, participants were randomly assigned with equal probability to one of three groups: [1] no activity prompts, [2] one activity prompt, or [3] two activity prompts. If a participant was assigned to the group receiving one activity prompt, it was sent at a random time between 8 am and 8 pm. If the participant was assigned to the group receiving two activity prompts, both prompts were sent at random times between 8 am and 8 pm. However, the time between the first and second prompts had to be at least three hours to avoid participant annoyance. The prompts were designed as motivational coaching messages to promote PA, based on BCTs. As previously specified in the design stage of the study, participants categorized as intenders received messages containing distinct BCTs compared to participants categorized as actors. Examples of message content can be found in the same section. Prior to sending a prompt, a pull request was submitted to the server hosting the application to verify the participant's step count. If the participant had not yet achieved their step goal, an activity prompt was delivered. The flow depicted in Figure 3 would subsequently be initiated. Conversely, if a participant had already achieved their daily step goal at the time the prompt was scheduled, a feedback message rather than an activity prompt was sent. Feedback messages were identical for all participants and limited to a maximum of one per day. Due to the research design employed, there was a possibility of participants being assigned to receive prompts on a specific day, but having already achieved their step goal before the scheduled prompt. As a result, these participants received fewer prompts than initially assigned, potentially leading to an uneven distribution of randomization across the experimental groups.

Throughout the study period, the server was monitored daily to determine the prompts received by each participant the previous day. The datafile was updated daily for each participant, including how many prompts they received, at which times the prompts were sent, whether they received feedback, and their daily step count. An overview of the dataset is provided in more detail in Appendix B.

Participants

Individuals were eligible to participate in the CLI program of Ancora Health when their body mass index (BMI) exceeded 30 and received a referral from their general practitioner to participate in the program. Additionally, possession of a pedometer, either in the form of a wearable device or smartphone, was necessary for inclusion in the program.

All individuals that were included in the CLI program offered by Ancora Health were eligible to participate in the study, provided they gave their consent for data analysis. Individuals who did not provide consent for data analysis were excluded from the study. Additionally, individuals who disabled push notifications in the application were also excluded. Finally, participants who did not synchronize their pedometer data with the application were excluded from study participation due to the unavailability of their step data.

Measures/outcomes

The purpose of the activity prompts was to augment the daily step count of the participants. Therefore, the primary (or proximal) outcome was the number of daily steps. This data was obtained with either a self-owned smartphone or a wearable, which both provide accurate step count tracking (87–89). However, caution should be exercised when interpreting smartphone step counts as they may underestimate steps, given that participants do not always carry their smartphones with them (90,91).

At baseline, several participant characteristics were obtained. These included baseline step count, phase of change, body mass index (BMI), age, and gender. Baseline step count was measured by calculating the average daily steps of the three weeks prior to the study start. Phase of change was, as described earlier, measured by assessing whether the step goal decreased for 2 consecutive weeks (i.e., intender) or not (i.e., actor). BMI was calculated by dividing weight in kilograms by the square of height in meters (kg/m^2) (92). Individuals could indicate whether they identified as being male, female, or nonbinary at the start of the program.

Statistical analysis

The statistical software R (v4.2.1) was used to perform the analyses (93,94). All analyses were conducted using the generalized estimating equations (GEE) method (95). The GEE method is particularly suitable for analyzing data with a nested or clustered structure, where observations within the same cluster or subject are likely to be more similar to each other than to observations from other clusters or subjects. This includes data from longitudinal studies, where repeated measurements are taken on the same individuals, such as the current study. The key idea behind GEE is to estimate the regression parameters by modeling the mean response using a working correlation structure that captures the within-cluster dependence. However, it should be noted that the GEE focuses on estimating sample-averaged effects of the covariates on the outcome, rather than subject-specific effects. So, while the GEE accounts for within-subject correlation, the estimated regression coefficients are considering all subjects. The GEE is considered a suitable method for analyzing longitudinal MRT data as it considers within-subject correlation and its capabilities to handle smaller clusters (58).

To account for the within-subject correlation, the dataset was initially sorted by participant number. Participant number was selected as "id" variable to identify the clusters. An exchangeable structure was used for the correlation matrix. This type of structure assumes all responses in a subject are equally correlated (96). Additionally, a histogram of the step count data was generated to assign the appropriate distribution. The distribution of step count data was evaluated since it is typically skewed to the right (59). Following consultation with a data expert of Ancora Health, the Poisson distribution was selected as the appropriate choice for the GEE model.

To assess the effect of the frequency and timing of the prompts sent, both the experimental groups, as well as the part of the day (i.e., morning, afternoon, evening) a prompt was sent were coded as factor variables, so R identifies the different levels of the variables. The experimental group variable consisted of three levels (i.e., 0, 1, or 2 prompts). The daypart variable consisted of 7 levels (i.e., morning, afternoon, evening, and all possible combinations of those). The same coding approach as in the MRT of Xu et al. (97) was used, in which the researchers also employed multiple intervention levels. In the GEE model that investigated the daily dose of prompts, step count was selected as the response variable and the experimental group was selected as the predictor variable. To examine the effects of prompt timing, the dataset was divided into two subsets before analysis. The first subset consisted of participant days where 1 prompt was received, categorized by timing: morning, afternoon, or evening. The second subset included participant days where two prompts were sent, with various combinations: morning and afternoon, morning and evening, or afternoon and evening. In the first subset, the morning prompt condition served as the reference group. In the second subset, the condition in which participants received both a morning and afternoon prompt served as the reference group. Two GEE models were then constructed to analyze each subset independently.

In the GEE models to investigate the timing of the prompts, step count was selected as the response variable and daypart (i.e., part of the day the prompt was sent) was selected as the predictor variable. Additionally, the day since the start of the study was included in both analyses to investigate whether there was a diminishing effect of the activity prompts, which has been shown in similar work (59,98). All rows containing missing data were excluded from the dataset before analysis.

The output of the model included the estimates for the intercept and all levels of the predictor variables. In the model assessing the daily dose of prompts sent, the intercept

represented the control condition. That is, the condition in which no prompts were sent. In the model assessing the timing when sending one prompt, the intercept represented the morning prompt group. In the model assessing the timing when sending two prompts, the intercept represented the group in which participants received one prompt in the morning and one prompt in the afternoon. The estimates of the other levels of the predictor variable were compared to the intercept. Additionally, the p-values were examined to either reject or accept the null hypotheses.
The estimate values were converted to the mean step counts to enhance interpretability of the results. First, the estimate of the experimental group was added to the estimate of the intercept and was subsequently exponentiated. Since the estimate represents the natural logarithm of the mean step count, taking the exponent restores the values to their original scale. The full R code used for data preparation and analysis can be found in Appendix C.

Sample size calculations were conducted using an MRT sample size calculator (99,100). It was assumed participants would be available for a notification 100% of the time, as they were expected to notice it at some point during the day it was sent. As mentioned, previous research found a diminishing intervention effect. Therefore, the effect size was assumed to decrease linearly from 0.2 to 0.15 over the study period. Based on this, the desired sample size was 48 participants with a power of 0.8 and a type-1 error rate of 5%.

Results

Participants

Initially, 30 individuals were recruited to participate in the technology-supported CLI of Ancora Health. One individual did not start the program in the application. Eight individuals dropped out of the program before the MRT started. Seven individuals didn't have a pedometer connected at the time of the start of the MRT and were therefore excluded from study participation. Fourteen individuals started the study procedure. The collected data revealed that one participant couldn't receive push notifications on the device used and was therefore excluded from data analysis. Figure 7 displays the participant flow diagram.

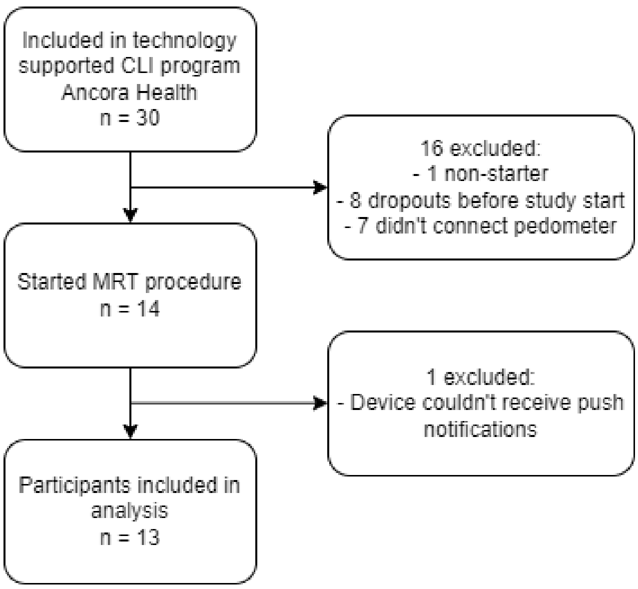

Figure 7. Participant flow diagram

The age of participants ranged from 38 years to 71 years (mean: 56,6 years; SD: 9,8 years). Three (23%) individuals identified as male; ten (77%) individuals identified as female. Based on baseline assessment, all 13 participants were categorized as actors. The baseline daily step count of the individuals ranged from 3940 steps to 16244 steps (median: 8419 steps; interquartile range: 4787 steps). The BMI of the participants ranged from 24,8 kg/m^2 to 41,6 kg/m^2 (mean: 31,0 kg/m^2; SD: 3,8 kg/m^2) at the start of the MRT. The baseline characteristics of the participants are presented in Table 4.

Table 4. Baseline characteristics participants (n=13)

Variable	**Value** *Mean (SD) or N (%)*
Age	56,6 years (9,8 years)
Gender - Male - Female - Nonbinary	 - 3 (23%) - 10 (77%) - 0 (0%)
Phase of change - Intender - Actor	 - 0 (0%) - 13 (100%)
BMI	31,0 kg/m^2 (3,8 kg/m^2)
Variable	**Value** *Median (interquartile range)*
Baseline step count	8419 steps (4787 steps)

Collected data

In total, data on 196 participant days was collected. 14 of those days contained missing step count values and were excluded. So, data analysis was conducted on 182 participant days. In those days, 169 coaching messages were sent. 69 of those messages were sent in the morning, 55 in the afternoon, and 45 in the evening. Participants were assigned to receive no prompts on 62 days, one prompt on 71 days, and two prompts on 49 days. The collected data on the messages that were sent is visualized in Figure 8.

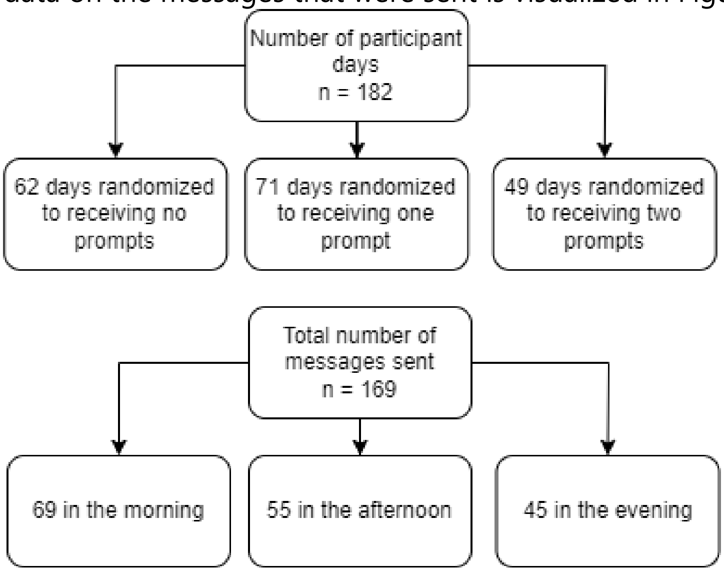

Figure 8. Randomization and prompt data

Effects of activity prompts

Daily dose

The initial analysis aimed to investigate the impact of daily prompt dosage on daily step count. The intercept in the model represents the 0 prompts group, with an estimated value of 9,03 (SE: 0,14). By exponentiating this estimate, the mean daily step count for the 0 prompts group was calculated to be 8350.

For the group receiving 1 activity prompt, the estimate was 0,23 (SE: 0,06). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 10509. A statistically significant difference was observed when comparing this group to the 0 prompts group ($p = <0{,}001$), suggesting that sending one activity prompt leads to a higher daily step count compared to not sending any activity prompts.

For the group receiving 2 activity prompts, the estimate was 0,08 (SE: 0,07). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 9045. No statistically significant difference was observed when comparing this group to the 0 prompts group ($p = 0{,}24$) suggesting that sending two activity prompts doesn't lead to a higher daily step count compared to not sending any activity prompts.

Additionally, days since the start of the MRT was included in the analysis. No statistical difference was observed ($p = 0{,}31$), suggesting that the effect of the activity prompts remained the same throughout the study period. Table 5 summarizes the results of the effects of the daily dose of activity prompts on daily step count.

Table 5. Results of GEE for daily dose of prompts and days since study start. Mean steps are exponentiation of the estimate of the GEE model. SE: standard error

Experimental group	**Estimate (SE)**	**Mean daily step count**	**p-value**
Intercept (0 prompts)	9,03 (0,14)	8350	
1 activity prompt	0,23 (0,06)	10509	<0,001*
2 activity prompts	0,08 (0,07)	9045	0,24
Covariate	**Estimate (SE)**		**p-value**
Days since start	-0,01 (0,01)		0,31

Timing when sending 1 activity prompt

The second analysis aimed to investigate the impact of activity prompt timing on daily step count. The intercept in the model represents the morning prompts group, with an estimated value of 9,34 (SE: 0,19). By exponentiating this estimate, the mean daily step count for the morning prompts group was calculated to be 11393.

For the group receiving 1 activity prompt in the afternoon, the estimate was -0,16 (SE: 0,12). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 9274. No statistically significant difference was observed when comparing this group to the morning prompts group ($p = 0{,}19$), suggesting that sending one activity prompt in the afternoon doesn't lead to a higher daily step count compared to sending one activity prompt in the morning.

For the group receiving 1 activity prompt in the evening, the estimate was -0,38 (SE: 0,11). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 7797. A statistically significant difference was observed when comparing this group to the morning prompts group ($p < 0{,}001$), suggesting

that sending one activity prompt in the evening leads to a lower daily step count compared to sending one activity prompt in the morning.
Additionally, days since the start of the MRT was included in the analysis. No statistical difference was observed (p = 0,88), suggesting that the effect of the activity prompts remained the same throughout the study period. Table 6 summarizes the results of the effects of the daily dose of activity prompts on daily step count.

Table 6. Results of GEE model for timing groups when receiving 1 prompt and days since study start. Mean steps are exponentiation of the estimate of the GEE model. SE: standard error

Daypart group	**Estimate (SE)**	**Mean steps**	**p-value**
Intercept (morning prompt)	9,34 (0,19)	11393	
Afternoon prompt	-0,16 (0,12)	9274	0,19
Evening prompt	-0,38 (0,11)	7797	<0,001*
Covariate	**Estimate (SE)**		**p-value**
Days since start	-0,002 (0,02)		0,88

Timing when sending 2 activity prompts
The third analysis aimed to investigate the impact of activity prompt timing on daily step count. The intercept in the model represents the group that received a morning and afternoon prompt, with an estimated value of 9,20 (SE: 0,14). By exponentiating this estimate, the mean daily step count for the 0 prompts group was calculated to be 9877.
For the group receiving 2 activity prompts, one in the morning and one in the evening, the estimate was -0,07 (SE: 0,07). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 9237. No statistically significant difference was observed when comparing this group to the morning and afternoon prompts group (p = 0,33), suggesting that sending two activity prompts in the morning and evening doesn't lead to a higher daily step count compared to sending activity prompts in the morning and afternoon.
For the group receiving 2 activity prompts, one in the afternoon and one in the evening, the estimate was 0,13 (SE: 0,14). After adding this estimate to the intercept and exponentiating the result, the mean step count for this group was determined to be 11210. No statistically significant difference was observed when comparing this group to the morning and afternoon prompts group (p = 0,36), suggesting that sending two activity prompts in the afternoon and evening doesn't lead to a higher daily step count compared to sending activity prompts in the morning and afternoon.
Additionally, days since the start of the MRT was included in the analysis. No statistical difference was observed (p = 0,18), suggesting that the effect of the activity prompts remained the same throughout the study period. Table 7 summarizes the results of the effects of the daily dose of activity prompts on daily step count.

Table 7. Results of the GEE model for timing groups when receiving 2 prompts and days since study start. Mean steps are exponentiation of the estimate of the GEE model. SE: standard error

Daypart group	**Estimate (SE)**	**Mean steps**	**p-value**
Intercept (morning + afternoon prompt)	9,20 (0,14)	9877	
Morning + evening prompt	-0,07 (0,07)	9237	0,33

Afternoon + evening prompt	0,13 (0,14)	11210	0,36
Covariate	**Estimate (SE)**		**p-value**
Days since start	-0,02 (0,02)		0,18

Discussion

Main findings

The main aim of this study was to systematically develop and evaluate a JITAI to promote PA in obese individuals. The first part of the study resulted in a first version of a JITAI that serves as an automated coaching system for participants of the technology supported CLI of Ancora Health. The second part of the study, the MRT, investigated how the activity prompts might be used to be most effective in promoting PA behaviors. This section provides an overview of the main findings of the current study, comparisons with similar research, strengths and limitations of this study and directions for future research.

The initial phase of the study involved the development of a first version of the JITAI. Both the program-planning framework of Kreuter and the JITAI framework of Nahum-Shani (57) were used to guide the design process. Adopting Kreuter's framework in intervention development can be highly effective in assisting individuals to change health behavior (63). Additionally, the JITAI framework has been demonstrated to be effective in improving PA behaviors (57). This approach ensured that the JITAI was grounded in behavioral theory, with a particular emphasis on incorporating evidence-based interventions through the utilization of several BCTs within the activity prompts. This is in contrast with previous research on JITAIs, as Hardeman et al. (42) reported that many JITAIs lack a theoretical basis and often contain only a limited number of BCTs. To ensure diversity and minimize repetition, a set of 91 tailored activity prompts was developed, aiming to mitigate participant annoyance. The prompts were tailored to part of the day, phase of change, and step goal achievement. Additionally, the prompts included both several SDT and PSD elements. After designing the intervention, it was successfully implemented in the Ancora Health application.

The MRT conducted in the second stage of the report revealed that the implementation of activity prompts can effectively enhance daily step count among obese individuals. Specifically, the findings indicate that sending a single activity prompt in the morning yields the most pronounced impact on promoting PA behaviors compared to the absence of activity prompts. Additionally, sending a single activity prompt in the evening resulted in significantly lower step counts compared to sending an activity prompt in the morning. Furthermore, the group exposed to two activity prompts exhibited a slightly higher average step count in comparison to the group without receiving any activity prompts, however, this difference did not reach statistical significance. Therefore, it can't be concluded that sending two activity prompts is effective in increasing daily step count in obese individuals. Moreover, none of the examined combinations of sending two prompts yielded a significant difference in step counts when compared to each other. That is, all combinations of sending two activity prompts are equally ineffective in increasing daily step count. However, it should be noted that the findings should be interpreted cautiously, as both the sample size and study duration were very limited.

Given the extensive body of research (101–104) demonstrating the positive impact of activity prompts on promoting PA behaviors, it was anticipated that the implementation of activity prompts in this study would also result in increased PA levels. However, these studies investigated general mHealth interventions, and were not defined as JITAIs. A JITAI is generally considered to be more personalized as it dynamically adapts intervention delivery based on real-time data and user characteristics (57). To date, only a limited number of MRTs have been conducted to investigate the effects of JITAIs utilizing prompts to enhance PA levels. Moreover, these MRTs have yielded inconsistent findings regarding the impact of activity suggestions on PA levels. For instance, Klasnja et al. (59) showed that sending three activity suggestions could add about 800 steps per day in healthy sedentary adults. The results partially align with the findings of the current study, as this study demonstrates a greater effectiveness of the activity prompts. Specifically, the results indicate that sending one activity prompt per day is associated with a significant increase in daily step count by an average of 2150 steps. Conversely, another study (61) found no effects of activity suggestions on daily step count in individuals after bariatric surgery. This could be explained by two reasons. First, the latter study employed SMS-messages to send activity suggestions and didn't have a native application. As a result, participants were unable to self-monitor their physical activity behavior, which limited their knowledge of their daily activity levels. This lack of self-monitoring may have potentially reduced the effectiveness of the activity suggestions. Additionally, the messages were only tailored to the time of the day and day of the week and did not consider behavioral theory or the step count. That is, the system might have sent more messages when a participant already reached their step goal, possibly causing irritation. Indeed, previous research has suggested that excessive prompt frequency can result in disengagement. (54,55). Second, the duration of the study was 16 weeks, whereas both the study conducted by Klasjna et al. (59) and the current study had comparatively shorter durations. The longer duration might have contributed to a diminishing intervention effect over time, which might be attributed to habituation to the messages (56). Finally, and potentially most importantly, neither of these JITAIs provided a theoretical foundation or employed BCTs within their interventions. This might explain the smaller effects observed in those studies, as the inclusion of behavioral theory and BCTs is consistently linked to greater intervention effectiveness (40,41).

Furthermore, the optimal frequency and timing of sending activity prompts was still unclear (50–53). This study contributes to the current literature by providing valuable insights into optimizing the delivery of activity prompts, considering both the minimal effective dose and timing for maximum effectiveness. Based on the results of the current study, sending an activity prompt in the morning or afternoon can be considered most effective. Sending a prompt in the evening might be too late for users which might prevent them from taking more steps. The findings of the MRT will be used to further develop the JITAI. For instance, a next version of the JITAI will presumably deliver a maximum of 1 activity prompt per day, either in the morning or in the afternoon.

Strengths

The current study has several strengths that contribute to the validity and reliability of the findings. First, the intervention development was guided by multiple well-established frameworks (57,63). Kreuter's program planning model offers a systematic approach for first analyzing the problem and subsequently identifying the relevant behavioral determinants

and BCTs to influence those determinants. The inclusion of behavioral determinants and BCTs in intervention development is associated with better outcomes of (health) behavior change interventions (105,106). The messages were written based on the identified BCTs in an attempt to maximize intervention effectiveness. Additionally, a large proportion of the messages were based on PSD principles. Including PSD principles in mHealth technologies have been shown to increase PA behaviors (107) and improve adherence (26) to the technology. Also, the messages targeted at providing the users a sense of autonomy, relatedness, and competence. Those are concepts derived from SDT and including those in the intervention has been shown to increase PA levels and exercise adherence (108,109). Furthermore, the components of a JITAI as described by Nahum-Shani were used in the intervention development. According to a recent meta-analysis (110), JITAIs demonstrated greater effectiveness in enhancing several health outcomes compared to alternative treatments or waitlist control groups. The authors adopted the components of Nahum-Shani in their search strategy for relevant studies. Thus, including those components is associated with higher intervention effectiveness in JITAIs.
Second, the intervention collected user data continuously and only passively. Too frequent active data collection increases user intervention burden, which is a primary determinant of reduced adherence and effectiveness (111). Additionally, adherence to active data collection methods, like ecological momentary assessment, exhibits variability and tends to decline over time (112). This decline in adherence poses a potential risk, as it may compromise the accuracy of the JITAI. Therefore, the decision was made to only employ passive data collection for the first version of the intervention, as this requires no input from the user.
Finally, a cutting-edge research design for evaluation of the intervention was employed. An MRT is highly efficient, as the repeated randomization of each individual allows statistical tests to balance bias and variance, enabling the assessment of treatment effects for both between-person and within-person. Therefore, this approach typically maintains statistical power while requiring fewer subjects compared to a fully between-subjects experiment (58,100). Additionally, as randomization is used to achieve compositional balance in unobserved and unknown factors, it enables the estimation of the causal effect of the treatment (113). Since micro-randomized trials repeatedly randomize intervention delivery, it can be evaluated how the intervention delivery effects change over time throughout the study.

Limitations

Besides the strengths, this study also has some limitations that reduce the validity and reliability of the findings.
First, the major limitations of this study were both the sample size and study duration. A small sample size leads to reduced statistical power, which affects the ability to draw meaningful conclusions from the data, and may result in spurious findings. The study's short duration is a limitation as it hinders the detection of long-term intervention effects, which is crucial given the challenge of behavior change maintenance in this research area (12). Additionally, the results may be influenced by chance, which is more likely with a smaller sample size and shorter study duration. To overcome this limitation, plans have already been made to conduct a study with more participants and longer duration.
Second, a limitation of the study design is that participants did not always receive their assigned number of prompts. For instance, if participants reached their step goal before the prompts were scheduled, they did not receive any prompts on that day. This resulted in an

uneven distribution of group assignments within the MRT analysis. Consequently, the group assigned to receive two prompts had a higher likelihood of having a lower step count for the day, as the prompts were only sent when participants had not reached their step goal yet. This variability in prompt delivery potentially influenced the observed results and introduced bias in the estimation of the intervention effect, which is important when interpreting the findings.

Third, only quantitative data was collected. It would have been valuable to also gather qualitative data from participants, for instance on their thoughts about the messages or on how the intervention might improve. This would provide additional information about why the intervention seems to be effective. Earlier research indicated that a participatory intervention development process increases technology adherence and might therefore lead to better health outcomes (114). Options to add questionnaires to the application in which the users can provide feedback on several features are already explored.

Fourth, the intervention is currently only poorly context-aware. That is, it doesn't consider the context of the individual besides the accumulated daily step count, phase of change, and part of the day. Previous JITAIs that did consider the context, included this in several modes. For instance, another JITAI included weather information to suggest inside or outside activity (115). Another JITAI recognized locations in which the user was generally active and used this information to send activity suggestions (38). This study showed that contextually tailored suggestions were more effective in increasing PA behaviors than generic messages. Opportunities to include more contextual information in the intervention are currently being explored. Additionally, personal preferences regarding type of physical activity (e.g., cycling, walking, swimming, etc.) could be included in a next version of the JITAI to foster autonomy of the users. According to SDT (83), an improved sense of autonomy could subsequently play a role in behavior maintenance.

Fifth, participants in the study were categorized to their phase of change based on their step goal achievement in the past two weeks. However, it should be noted that this method has not been validated. This raises uncertainty about the validity of this categorization method. Without a validated method, there is a risk of misclassifying participants into incorrect phases of change, potentially introducing bias or inaccuracies in the study results. Therefore, the findings regarding the impact of different phases of change on the outcomes should be interpreted with caution due to the uncertain validity of the categorization method employed.

Sixth, multiple methods were employed to measure the step count of the participants. Some participants used their phones to measure step count, while others used a wearable. Using multiple methods to measure step counts may decrease measurement reliability due to increased variability between the employed methods. Efforts are made to provide every participant with the same wearable to increase reliability of the step count measurement.

Seventh, only the daily step count was assessed. Similar research (59) investigated the effectiveness of activity suggestions on the step count in the 30 minutes after a suggestion was sent. This could provide more information on the proximal effect of the suggestion. When only investigating daily step count data, it is more plausible that other variables influenced the step count as well. For instance, participants' overall activity levels, environmental factors, or personal circumstances, may have influenced the step count throughout the day, potentially masking the specific impact of the activity suggestion. Therefore, investigating the step count in the immediately after the suggestion can provide more targeted information on the direct effects of the suggestion itself.

Future research

Follow-up studies should focus on several aspects. A longer study duration combined with an increased sample size can enhance the robustness of the obtained results, which facilitates the derivation of more conclusive outcomes. Furthermore, a longer study duration can facilitate the examination of potential long-term effects associated with sending activity prompts, as these remain unclear (110). This topic remains underexplored, as previous research has reported limited information on the effects of behavior change interventions on long-lasting behavior maintenance (116).

Regarding the intervention, various aspects can be explored. For example, research efforts could focus on investigating methods to make the intervention more context-aware, thereby promoting greater personalization within the intervention. For instance, weather and location information can be included in the intervention. Research can also focus on which additional contextual variables might increase intervention effectiveness.

Finally, artificial intelligence techniques such as reinforcement learning (RL) can be applied to the JITAI to provide more contextually-relevant activity prompts. Previous studies (117,118) employed RL to optimize the delivery of both activity and feedback prompts. Yom-Tov et al. (117) developed an RL algorithm that took the demographics, past activity, expected activity, and message history into account. The effectiveness of a message was evaluated by calculating the amount of PA after the message and this was used as a reward for the algorithm. They found that this algorithm was more effective than unvarying weekly reminders to promote PA behaviors. Additionally, Liao et al. (118) developed an RL algorithm that used both the context of the user and a summary of past history to determine randomization probabilities for sending an activity prompt. They hypothesize that this algorithm will be effective in promoting PA behaviors after preliminary validation.

Conclusions

This study showed that a systematically developed JITAI that sends activity prompts might be effective in promoting PA behaviors in obese individuals. Specifically, the findings suggest that sending one daily activity prompt in the morning seems most effective to increase daily step counts. These findings can inform the further optimization of the currently developed JITAI, which could subsequently lead to better (health) outcomes. The MRT results contribute to the existing literature by demonstrating the potential of systematically developed JITAIs with activity prompts to enhance PA behaviors. The study also highlights the importance of considering the optimal timing and frequency of activity prompts. Furthermore, the study identified the need for more research on the effects of JITAIs employing prompts to promote PA. Previous studies have provided inconsistent findings, potentially attributed to variations in intervention delivery methods and study durations. Future research should explore the long-term effects and optimal strategies, such as RL techniques, for delivering activity prompts within JITAIs.

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Appendix A – Coaching messages

Nr	Phase	Time	Title	Body	BCT employed
1	Intender	Morning	Today's step goal	Good morning <name>! Today's step goal is <step goal>. Planning physical activity moments will help you achieve your goal!	AP 1.4
2	Intender	Morning	A tip to achieve your goal	Think about how you deal with moments when it's difficult to stay active. Remember why you started and what your goal is!	CP 1.2
3	Intender	Morning	Planning difficult moments	This helps you achieve your goal. For example: if it rains today, I will increase my indoor physical activity.	CP 1.2
4	Intender	Morning	A little support	If we want to move more, there are always better and worse days. We have confidence that you'll make today a good day!	VPC 15.1
5	Intender	Morning	Making an exercise plan	Good morning <name>! Try to make your plan to be active as specific as possible. Think about when, where, and how you will do this!	AP 1.4
6	Intender	Morning	Making an exercise plan	Good morning <name>! Choose a moment in advance when you want to exercise today. This will increase your chances of achieving your goals!	AP 1.4
7	Intender	Morning	A tip to achieve your goal	If things have been going a bit rough lately, that's okay. Think about the things that went well, as it will help you to rebuild again!	RNE 7.3
8	Intender	Morning	A tip to achieve your goal	Good morning <name>! Plan for yourself how you will be active today. For example: I will take the stairs instead of the elevator.	AP 1.4
9	Intender	Morning	Making an exercise plan	Good morning <name>! Make your plan concrete by deciding when, where, and how you will exercise. This increases your chances of success!	AP 1.4
10	Intender	Morning	Making an exercise plan	What are you going to do today to achieve your goal? It helps to describe for yourself what you want to do and for how long!	AP 1.4
11	Intender	Morning	Making an exercise plan	Schedule moments when you want to move in your calendar in advance. This way, the chances are higher that you will actually do it!	AP 1.4
12	Intender	Morning	A tip to achieve your goal	Think ahead about how you will handle challenges, such as a busy day at work. Plan solutions that will help you stay active regardless.	CP 1.2
13	Intender	Morning	Dealing with difficult moments	Good morning <name>! When you don't feel like exercising, ask someone to join you. This helps as a support!	CP 1.2

14	Intender	Morning	Dealing with obstacles	If something comes up and you have to reschedule an activity you had planned, make a deal with yourself to move it no more than 2 days.	CP 1.2
15	Intender	Afternoon	Dealing with obstacles	Is the weather bad when you have planned an activity? Make sure to prepare an umbrella or raincoat in advance, so you can still go!	CP 1.2
16	Intender	Afternoon	What do you like to do?	Hi <name>! Choose activities that you enjoy. This will give you energy instead of costing you energy!	AP 1.4
17	Intender	Afternoon	A tip to stay active	Stick a post-it note on places where you often sit for a long time to remind you to stand up more. This will help you to be more active!	AP 1.4
18	Intender	Afternoon	Making movement more fun	Listen to your favorite music or podcast during your activity. This makes it more enjoyable and helps you stick with it!	AP 1.4
19	Intender	Afternoon	A benefit of exercise	An afternoon walk helps you to feel more energetic and also to reach your step goal for today! Make a plan and go for it!	AP 1.4
20	Intender	Afternoon	Making an exercise plan	Hi <name>! Plan for yourself on which day and where you want to exercise. This helps you to actually do it!	AP 1.4
21	Intender	Afternoon	Making an exercise plan	Hi <name>! When you haven't taken many steps yet, don't worry. Try to make a plan, there is still plenty of time!	AP 1.4
22	Intender	Afternoon	A benefit of exercise	An afternoon walk can help you have less stress for the rest of the day. If you have little time, even a short walk can have an effect!	GT 8.7
23	Intender	Afternoon	Dealing with difficult moments	If it's hard to achieve your step goal today, remind yourself of why you started. This can help you to still achieve your goal!	CP 1.2
24	Intender	Afternoon	Today's step goal	Hi <name>! On track with your step goal? Some physical activity can help you reach it!	SM 2.3
25	Intender	Afternoon	A tip to achieve your goal	Try to go for a walk with someone today. It's a fun activity and can help you reach your step goal!	SS 3.1
26	Intender	Afternoon	A tip to achieve your goal	Hi <name>! Start with small steps. Taking an extra walk around the block each day already contributes to a healthier lifestyle!	GT 8.7
27	Intender	Afternoon	A tip to achieve your goal	Hi <name>! A clear plan is the key to success. Set it up by scheduling your activity in your calendar in advance!	AP 1.4
28	Intender	Afternoon	A tip to achieve your goal	Hi <name>! Take a moment to create your exercise plan. Determine specifically what you will do to achieve your goal.	AP 1.4
29	Intender	Afternoon	A tip to achieve your goal	Hi <name>! Short on time? Try a quick workout at home to stay active and reach your activity goal!	CP 1.2

30	Intender	Afternoon	A tip to achieve your goal	Hi <name>! Plan ahead for how to deal with a slump: "If I don't feel like exercising, I'll call a friend to work out together."	CP 1.2
31	Intender	Evening	Making walking more fun	Hi <name>! Look up a nice hiking trail nearby and turn it into a fun outing. This way, you'll enjoy exercising more!	AP 1.4
32	Intender	Evening	Today's step goal	If you didn't reach your step goal yet, don't worry, it happens. Plan to take some time tonight to get as close to your goal as possible!	AP 1.4
33	Intender	Evening	A tip to achieve your goal	Think back to the times when you achieved your goal. What did you do then? Try doing that again now to reach your goal!	FOPS 15.3
34	Intender	Evening	Setting goals	Hi <name>! For tomorrow, set a small goal for each daypart. For example, "I want to walk at least 15 minutes in each part of the day."	GS 1.1
35	Intender	Evening	Step goal not achieved yet?	Remember why you started this challenge and where you want to go. This will help you achieve your goal anyway!	CP 1.2
36	Intender	Evening	A tip to achieve your goal	Hi <name>! It can be fun to go out with someone else tonight to clear your head!	SS 3.1
37	Intender	Evening	A tip to achieve your goal	We don't always feel like moving, but we usually feel better afterwards! Going for a walk with someone else can help clear your mind.	SS 3.1
38	Intender	Evening	Tomorrow is another day!	It's okay if you have been struggling to reach your goals lately, we all go through rough patches.	RNE 7.3
39	Intender	Evening	Making an exercise plan	This is crucial to actually follow through with it. Describe when, where, and how you will be physically active tomorrow!	AP 1.4
40	Intender	Evening	Making an exercise plan	It helps to plan activity for tomorrow in advance if you are having trouble reaching your goals. When will you be exercising tomorrow?	AP 1.4
41	Intender	Evening	A tip to achieve your goal	Think in advance about how you deal with fatigue. Plan your activity, for example, at a time when you are normally energetic!	CP 1.2
42	Intender	Evening	A tip to achieve your goal	If it's difficult to move enough, try setting an alarm for tomorrow at a time when you have time to be active.	AP 1.4
43	Actor	Morning	A tip to stay active	Active transportation is a good way to move more. For example, take the bike instead of the car for your groceries!	AP 1.4
44	Actor	Morning	A tip to achieve your goal	Good morning <name>! Try to keep track of how many steps you have taken today. This can help you achieve your goal!	SM 2.3
45	Actor	Morning	A tip to achieve your goal	It helps to break down your step goal into several small goals today. For example, try to do something active every part of day.	GS 1.1

46	Actor	Morning	You're doing well!	Good morning <name>! You've been doing well lately. Are you going to achieve your goal again today?	FB 2.2
47	Actor	Morning	You're doing well!	Good morning <name>! You're doing well lately, keep up the good work!	FB 2.2
48	Actor	Morning	Together is more fun than alone!	Good morning <name>! It can be helpful to take a walk with someone today to be active and have some fun!	SS 3.1
49	Actor	Morning	A tip to achieve your goal	Good morning <name>, preparation helps you achieve your goals. Check the weather forecast and plan your activity when it's nice outside!	IPB 4.1
50	Actor	Morning	A tip to achieve your goal	Good morning <name>, starting the day with a short walk can give you an extra energy boost for the rest of the day.	GT 8.7
51	Actor	Morning	A tip to achieve your goal	Good morning <name>! Forming habits can help you achieve your goals, like taking a short walk every morning for example!	HF 8.3
52	Actor	Morning	You're doing great <naam>!	Good morning <name>! You've been doing great lately, I'm sure you'll continue that streak today!	VPC 15.1
53	Actor	Morning	Together is more fun than alone!	Good morning <name>! Tell someone else that you want to move today. Maybe they want to join you!	SS 3.1
54	Actor	Morning	A tip to achieve your goal	Active choices help to improve your lifestyle. For example, take the stairs or park your car a little further away!	HF 8.3
55	Actor	Morning	A tip to achieve your goal	Make exercise part of your morning routine. By starting your day with movement, you immediately start with a healthy habit!	HF 8.3
56	Actor	Morning	Give yourself the time.	It usually takes a few weeks for a new activity to become a habit, so don't give up if it doesn't work out once.	HF 8.3
57	Actor	Morning	Tracking your goals	Good morning <name>! By tracking your physical activity, you can gain better insight into your habits and how to improve them.	SM 2.3
58	Actor	Morning	Habit formation	Good morning <name>! Did you know that forming habits takes 6-8 weeks? Repeatedly performing a behavior is therefore very important!	HF 8.3
59	Actor	Morning	A tip to achieve your goal	Do you have friends who like to exercise? Ask them what they do to maintain their motivation, it might help you too!	SS 3.1
60	Actor	Morning	Planning to deal with obstacles	For example, make an appointment with a colleague to go for a walk. This way you can have a meeting and be active at the same time!	CP 1.2
61	Actor	Afternoon	Today's step goal	Hi <name>! How many steps have you taken today? Maybe you can plan a walk today to achieve your goal!	SM 2.3

62	Actor	Afternoon	Making an exercise plan	Hi <naam>! When are you planning to be active today? Make it specific: where, when, and how are you going to do it?	AP 1.4
63	Actor	Afternoon	Step goal not achieved yet?	Try setting a smaller goal for yourself. This way you can still come close to or even achieve your step goal!	GS 1.1
64	Actor	Afternoon	Habit formation	Hi <name>! Try to take a short walk around the same time every day. Habits help you stay more active!	HF 8.3
65	Actor	Afternoon	A tip to achieve your goal	Small adjustments can lead to big results. For example, park your car a little further from your destination and walk the rest of the way.	HF 8.3
66	Actor	Afternoon	You're doing great <naam>!	Hi <name>! Your habit of being active every day will definitely have a positive impact on your fitness, keep it up!	FB 2.2
67	Actor	Afternoon	A benefit of exercise	Hi <name>! Do you also feel so good after a walk?	ST 15.4
68	Actor	Afternoon	Other benefits of exercise	Try not to always be guided by the number of steps you take. Feeling better is also progress!	RNE 7.3
69	Actor	Afternoon	A benefit of exercise	Fresh air gives new energy! Make a specific plan for where and when you want to walk and do it when it suits you!	AP 1.4
70	Actor	Afternoon	A tip to achieve your goal	Hi <name>! Do you already have a walking buddy? Exercising together is more fun than alone!	SS 3.1
71	Actor	Afternoon	You're doing great <name>!	Hi <name>! Your loved ones are surely proud of the journey you have embarked on, keep it up!	IOOA 6.3
72	Actor	Afternoon	What's your goal?	Hi <name>! Reminding yourself why you are doing this will help you stay motivated!	ST 15.4
73	Actor	Afternoon	Habit formation	By regularly exercising at the same time, you create a habit and it becomes easier to stick to it.	HF 8.3
74	Actor	Afternoon	Habit formation	Make physical activity a regular part of your daily routine. For example, plan a lunchtime walk or go exercise after work.	HF 8.3
75	Actor	Afternoon	You're doing great <name>!	Hi <name>! Be proud of every step you take in the right direction, big or small. You're on the right track!	VPC 15.1
76	Actor	Afternoon	Stay positive	Don't focus on what you haven't achieved yet, but think about the times when you were successful in achieving your exercise goals!	FOPS 15.3
77	Actor	Afternoon	Stay positive	Achieving your goal can be difficult at times, but look back on the moments when you were successful and use them as motivation!	FOPS 15.3
78	Actor	Afternoon	A tip to achieve your goal	Spending time with friends or family and being more active can go together! Consider planning a walk or bike ride together, for example.	SS 3.1

79	Actor	Evening	Dealing with little energy	If you have little energy in the evening to exercise, try to plan it at times when you normally feel more energetic.	CP 1.2
80	Actor	Evening	Today's step goal	Good evening <name>! How many steps have you taken today? Maybe you can still reach your goal tonight!	SM 2.3
81	Actor	Evening	Stay positive	When you haven't reached your step goal yet, think about the times you did before. This will give you extra motivation!	FOPS 15.3
82	Actor	Evening	Step goal not achieved yet?	That's okay. Maybe you can take a short walk tonight, otherwise there's a new day tomorrow!	RNE 7.3
83	Actor	Evening	Habit formation	Walking outside for a short distance every evening may seem like it's not a lot, but it positively impacts your health!	HF 8.3
84	Actor	Evening	Stay positive	Don't worry if you've been less active today than usual, you've been doing great lately!	RNE 7.3
85	Actor	Evening	A tip to achieve your goal	Hi <name>! Share with others that you are trying to move more. Perhaps they can help you in achieving your goal!	SS 3.1
86	Actor	Evening	A benefit of exercise	By taking a short walk in the evening, you can accomplish two things at once: sleeping better and reaching your step goal!	IOHC 5.1
87	Actor	Evening	Stay positive	Progress doesn't always happen in a straight line. Sometimes you have to take a step back, but that's normal and helps to grow and learn.	RNE 7.3
88	Actor	Evening	Stay positive	Hi <name>! A less active day can happen and it's okay, just try to continue where you left off tomorrow!	RNE 7.3
89	Actor	Evening	Setting goals	If your step goal seems too big, break it down into several small goals. These are easier to achieve and will keep you motivated!	GT 8.7
90	Actor	Evening	You're doing great <name>!	You have shown many times recently that you can achieve your goals, use this as motivation to keep going!	FOPS 15.3
91	Actor	Evening	Setting goals	Good evening <name>! Reward yourself after each achieved goal, big or small. For example, with a warm shower or a healthy snack!	GT 8.7

Appendix B – Overview dataset

	ASN	PartNumber	Gender	Age	BMI	BaselineStepCount	PhaseOfChange	DaysSinceStart	ExpGroup	NoPrompt	OnePrompt	TwoPrompts	Timefirst	Timesecond	MorningPrompt	NoonPrompt	EvePrompt	DaypartGroup	StepCount
1	5JzSOyRnFYD3ZdXR8v5k8H	1	Male	47	31.7	7663	Actor	1	2	0	0	1	8	18	1	0	1	5	4301
2	4HcHnXtLcvAuXhibwOxCGD	2	Male	62	30.2	16244	Actor	1	1	0	1	0	13	0	0	1	0	2	13566
3	1I98rP2mNNi9TuyNFrvXiG	3	Female	71	30.0	6129	Actor	1	1	0	1	0	19	0	0	0	1	3	5897
4	28olvvqzjK2TzprZihbH6R	4	Male	47	28.7	NA	Intender	1	NA	NA	NA	NA	0	0	0	0	0	0	NA
5	1hOVt8ZxKMT0sVQMJOqxj5	5	Female	67	31.5	3940	Actor	1	2	0	0	1	11	19	1	0	1	5	5087
6	67tFMscvjTvn3cdvuHIfyG	6	Female	66	27.3	8787	Actor	1	0	1	0	0	0	0	0	0	0	0	10837
7	44TI5BcTj2xV9SkJRMyahC	7	Male	68	24.8	9816	Actor	1	1	0	1	0	12	0	0	1	0	2	11411
8	3vQQ0NDIEeRed8dDnAgel6	8	Female	55	32.5	14116	Actor	1	2	0	0	1	15	20	0	1	1	6	15398
9	460InvtvgaBiAwkgwYivTH	9	Female	56	28.7	10916	Actor	1	2	0	0	1	11	17	1	0	1	5	8385
10	7NS1tf26D5oC4c1ZSHuWMe	10	Female	60	29.6	8418	Actor	1	0	1	0	0	0	0	0	0	0	0	5393
11	4b09D7DGz12bF0WISCKqnh	11	Female	56	33.2	6645	Actor	1	0	1	0	0	0	0	0	0	0	0	3202
12	6DEF2NRQa8xKvC6E9hf3Rd	12	Female	38	31.3	11557	Actor	1	1	0	1	0	10	0	1	0	0	1	32465
13	56V95gM5CixINDA2XQLeKT	13	Female	45	32.2	3942	Actor	1	0	1	0	0	0	0	0	0	0	0	5664
14	42OqIBmc2DBiZ9XchHf5j3	14	Female	54	41.6	4570	Actor	1	0	1	0	0	0	0	0	0	0	0	4599
15	5JzSOyRnFYD3ZdXR8v5k8H	1	Male	47	31.7	7663	Actor	2	1	0	1	0	17	0	0	0	1	3	7281
16	4HcHnXtLcvAuXhibwOxCGD	2	Male	62	30.2	16244	Actor	2	2	0	0	1	14	19	0	1	1	6	19873
17	1I98rP2mNNi9TuyNFrvXiG	3	Female	71	30.0	6129	Actor	2	0	1	0	0	0	0	0	0	0	0	6977
18	28olvvqzjK2TzprZihbH6R	4	Male	47	28.7	NA	Intender	2	NA	NA	NA	NA	0	0	0	0	0	0	NA
19	1hOVt8ZxKMT0sVQMJOqxj5	5	Female	67	31.5	3940	Actor	2	0	1	0	0	0	0	0	0	0	0	6388
20	67tFMscvjTvn3cdvuHIfyG	6	Female	66	27.3	8787	Actor	2	1	0	1	0	11	0	1	0	0	1	6322
21	44TI5BcTj2xV9SkJRMyahC	7	Male	68	24.8	9816	Actor	2	1	0	1	0	10	0	1	0	0	1	10190
22	3vQQ0NDIEeRed8dDnAgel6	8	Female	55	32.5	14116	Actor	2	0	1	0	0	0	0	0	0	0	0	16908
23	460InvtvgaBiAwkgwYivTH	9	Female	56	28.7	10916	Actor	2	1	0	1	0	16	0	0	1	0	2	6866
24	7NS1tf26D5oC4c1ZSHuWMe	10	Female	60	29.6	8418	Actor	2	1	0	1	0	9	0	1	0	0	1	7951
25	4b09D7DGz12bF0WISCKqnh	11	Female	56	33.2	6645	Actor	2	0	1	0	0	0	0	0	0	0	0	1214
26	6DEF2NRQa8xKvC6E9hf3Rd	12	Female	38	31.3	11557	Actor	2	2	0	0	1	13	17	0	1	1	6	5278
27	56V95gM5CixINDA2XQLeKT	13	Female	45	32.2	3942	Actor	2	1	0	1	0	9	0	1	0	0	1	9001
28	42OqIBmc2DBiZ9XchHf5j3	14	Female	54	41.6	4570	Actor	2	1	0	1	0	11	0	1	0	0	1	7312
29	5JzSOyRnFYD3ZdXR8v5k8H	1	Male	47	31.7	7663	Actor	3	1	0	1	0	11	0	1	0	0	1	7381
30	4HcHnXtLcvAuXhibwOxCGD	2	Male	62	30.2	16244	Actor	3	1	0	1	0	9	0	1	0	0	1	20246
31	1I98rP2mNNi9TuyNFrvXiG	3	Female	71	30.0	6129	Actor	3	1	0	1	0	12	0	0	1	0	2	11800
32	28olvvqzjK2TzprZihbH6R	4	Male	47	28.7	NA	Intender	3	NA	NA	NA	NA	0	0	0	0	0	0	NA
33	1hOVt8ZxKMT0sVQMJOqxj5	5	Female	67	31.5	3940	Actor	3	0	1	0	0	0	0	0	0	0	0	5535
34	67tFMscvjTvn3cdvuHIfyG	6	Female	66	27.3	8787	Actor	3	1	0	1	0	9	0	1	0	0	1	11298
35	44TI5BcTj2xV9SkJRMyahC	7	Male	68	24.8	9816	Actor	3	1	0	1	0	14	0	0	1	0	2	11369
36	3vQQ0NDIEeRed8dDnAgel6	8	Female	55	32.5	14116	Actor	3	2	0	0	1	10	17	1	0	1	5	9821
37	460InvtvgaBiAwkgwYivTH	9	Female	56	28.7	10916	Actor	3	1	0	1	0	10	0	1	0	0	1	16290

ASN	PartNumber	Gender	Age	BMI	BaselineSt	PhaseOfChange
5JzSOyRnFYD3ZdXR8v5k8H	1	Male	47	31,7	7662,767	Actor
4HcHnXtLcvAuXhibwOxCGD	2	Male	62	30,2	16243,57	Actor
1I98rP2mNNi9TuyNFrvXiG	3	Female	71	30	6128,867	Actor
1hOVt8ZxKMT0sVQMJOqxj5	5	Female	67	31,5	3940,267	Actor
67tFMscvjTvn3cdvuHIfyG	6	Female	66	27,3	8786,967	Actor
44Tl5BcTj2xV9SkJRMyahC	7	Male	68	24,8	9815,833	Actor
3vQQ0NDlEeRed8dDnAgel6	8	Female	55	32,5	14115,7	Actor
460InvtvgaBiAwkgwYivTH	9	Female	56	28,7	10916,27	Actor
7NS1tf26D5oC4c1ZSHuWMe	10	Female	60	29,6	8418,5	Actor
4b09D7DGz12bF0WISCKqnh	11	Female	56	33,2	6644,533	Actor
6DEF2NRQa8xKvC6E9hf3Rd	12	Female	38	31,3	11556,77	Actor
56V95gM5CixINDA2XQLeKT	13	Female	45	32,2	3942,433	Actor
42OqlBmc2DBiZ9XchHf5j3	14	Female	54	41,6	4569,6	Actor

Variable	Value	Mean	SD	N	%
Age		57,3076923	9,79272362		
Gender					
	Male			3	23,07692
	Female			10	76,92308
	Nonbinary			0	0
Phase of change					
	Intender			0	0
	Actor			13	100
Baseline step count		8672,46667	3817,62821		
BMI		31,1230769	3,90024654		

Participan	Stepgoal24	Stepgoal17	Stepgoal10		PoC
1	7000	6500	6000		Actor
2	12000	11500	11000		Actor
3	8500	8000	8500		Actor
5	6000	6000	5500		Actor
6	6000	5500	5000		Actor
7	9000	8500	8000		Actor
8	11500	12000	12000		Actor
9	9500	9500	9000		Actor
10	11500	11000	11000		Actor
11	7500	7000	6500		Actor
12	10500	11000	10500		Actor
13	5000	5000	5000		Actor
14	4500	4000	4500		Actor

Participan	Steps	Steps2wee	Steps3weeks		BaselineStepCount
1	6764	7844,7	8379,6		7662,767
2	15697	18092,1	14941,6		16243,57
3	5292,6	6348	6746		6128,867
4	4049,9	3622	4148,9		3940,267
5	9748,6	8114,6	8497,7		8786,967
6	9146,7	10325,1	9975,7		9815,833
7	12770,1	13339	16238		14115,7
8	10646,4	11898,3	10204,1		10916,27
9	6662,6	8108,9	10484		8418,5
10	6799,7	6123,5	7010,4		6644,533
11	12085,3	11758,7	10826,3		11556,77
12	3616,4	3510,3	4700,6		3942,433
13	3725,9	3725,9	6257		4569,6

Appendix C – R code

```
library(readxl)
library(geepack)
library(dplyr)
library(ggplot2)

#Load data
Data <- read_excel("###############")

#Delete rows with missing data
Data <- na.omit(Data)

#Sort data on DaysSinceStart, PartNumber, and ExpGroup
Data <- Data%>%
  arrange(PartNumber)


#Histogram of step data
hist(Data$StepCount, main = "Histogram of step count", xlab = "Step count")
plot(density(Data$StepCount, na.rm = TRUE))

#Count in which group participants were randomized
table(Data$ExpGroup)
table(Data$DaypartGroup)

#Count the number of prompts that were sent
table(Data$Timefirst)
table(Data$Timesecond)

#Calulate median and IQR of baseline stepcount
median(Data$BaselineStepCount)
IQR(Data$BaselineStepCount)


###################Daily dose of prompts################
# Convert ExpGroup to a factor variable
Data$ExpGroup <- as.factor(Data$ExpGroup)

#Fit GEE model for experimental group (daily dose of prompts)
ModelDose <- geeglm(StepCount ~ ExpGroup + DaysSinceStart, data = Data, id =
PartNumber, family = poisson, corstr = "exchangeable")
summary(ModelDose)

####################Timing of prompts###################

#Create subset of the data containing only groups receiving 1 prompt
Data1 <- subset(Data, DaypartGroup < 4)
```

```
Data1$DaypartGroup <- ifelse(Data1$DaypartGroup == 1, 0,
                    ifelse(Data1$DaypartGroup == 2, 1,
                        ifelse(Data1$DaypartGroup == 3, 2,
                            ifelse(Data1$DaypartGroup == 0, NA, Data1$DaypartGroup))))


#Convert DaypartGroup to factor variable
Data1$DaypartGroup <- as.factor(Data1$DaypartGroup)

#Remove NA's
Data1 <- na.omit(Data1)

#Fit GEE model for timing of prompts when sending 1 prompt
ModelTiming1 <- geeglm(StepCount ~ DaypartGroup + DaysSinceStart, data = Data1, id =
PartNumber, family = poisson, corstr = "exchangeable")
summary(ModelTiming1)

#Create subset of data containing only groups receiving 2 prompts
Data2 <- subset(Data, DaypartGroup %in% c(0, 4, 5, 6))
Data2$DaypartGroup <- ifelse(Data2$DaypartGroup == 4, 0,
                    ifelse(Data2$DaypartGroup == 5, 1,
                        ifelse(Data2$DaypartGroup == 6, 2,
                            ifelse(Data2$DaypartGroup == 0, NA, Data2$DaypartGroup))))


#Convert Daypartgroup to factor variable
Data2$DaypartGroup <- as.factor(Data2$DaypartGroup)

#Remove NA's
Data2 <- na.omit(Data2)

#Fit GEE model for timing of prompts when sending 2 prompt
ModelTiming2 <- geeglm(StepCount ~ DaypartGroup + DaysSinceStart, data = Data2, id =
PartNumber, family = poisson, corstr = "exchangeable")
summary(ModelTiming2)

################Mean step counts for groups#################
#Mean step counts for dose and timing
Data %>%
  group_by(NoPrompt, OnePrompt, TwoPrompts) %>%
  summarise(mean_step_count = mean(StepCount))

Data %>%
  group_by(MorningPrompt, NoonPrompt, EvePrompt) %>%
  summarise(mean_step_count = mean(StepCount))

#Visualization mean step count dose and timing
```

```
ggplot(data = Data, aes(x = factor(ExpGroup), y = StepCount)) +
  geom_bar(stat = "summary", fun = "mean", fill = "steelblue") +
  labs(x = "Experimental Group", y = "Step Count", title = "Mean Step Count by Experimental
Group")


ggplot(data = Data, aes(x = factor(DaypartGroup), y = StepCount)) +
  geom_bar(stat = "summary", fun = "mean", fill = "steelblue") +
  labs(x = "Experimental Group", y = "Step Count", title = "Mean Step Count by Experimental
Group")


#################################Plotting data for
dose###############################################

# Create a new column for group
Data$ExpGroupText <- ifelse(Data$ExpGroup == 0, "NoPrompt",
                 ifelse(Data$ExpGroup == 1, "OnePrompt", "TwoPrompts"))

# Define color palette
my_colors <- c("NoPrompt" = "#FF5252", "OnePrompt" = "#4CAF50", "TwoPrompts" =
"#2196F3")

# Plot the data with color-coded groups
ggplot(data = Data, aes(x = DaysSinceStart, y = StepCount, color = ExpGroupText)) +
  geom_point() +
  scale_color_manual(values = my_colors) +
  geom_smooth(method = "lm", se = FALSE)

# Plot the boxplot of step data by experimental group
ggplot(data = Data, aes(x = ExpGroup, y = StepCount, fill = ExpGroupText)) +
  geom_boxplot(width = 0.5, outlier.shape = NA) +
  scale_fill_manual(values = my_colors) +
  labs(x = "Group", y = "Step Count", title = "Step Count by Group") +
  theme_minimal() +
  theme(plot.title = element_text(size = 16, face = "bold"),
        axis.title = element_text(size = 14),
        axis.text = element_text(size = 12),
        legend.title = element_blank(),
        legend.text = element_text(size = 12),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_blank(),
        panel.border = element_blank())


###################Plotting data for timing when sending 1 prompt##########
```

```
Data1$DaypartGroupText <- ifelse(Data1$DaypartGroup == 0, "NoPrompt",
                   ifelse(Data1$DaypartGroup == 1, "Morning",
                      ifelse(Data1$DaypartGroup == 2, "Noon",
                         "Evening")))

my_colors1 <- c("NoPrompt" = "red", "Morning" = "light blue", "Noon" = "green", "Evening"
= "purple")

# Plot the boxplot of stepcount data by daypart
ggplot(data = Data1, aes(x = DaypartGroup, y = StepCount, fill = DaypartGroupText)) +
 geom_boxplot(width = 0.5, outlier.shape = NA) +
 scale_fill_manual(values = my_colors1) +
 labs(x = "Group", y = "Step Count", title = "Step Count by Group") +
 theme_minimal() +
 theme(plot.title = element_text(size = 16, face = "bold"),
    axis.title = element_text(size = 14),
    axis.text = element_text(size = 12),
    legend.title = element_blank(),
    legend.text = element_text(size = 12),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    panel.background = element_blank(),
    panel.border = element_blank())


##############Plotting data for timing when sending 2 prompts###########

Data2$DaypartGroupText <- ifelse(Data2$DaypartGroup == 0, "NoPrompt",
                    ifelse(Data2$DaypartGroup == 4, "Morning + Noon",
                     ifelse(Data2$DaypartGroup == 5, "Morning + Evening",
                       "Noon + Evening")))

my_colors2 <- c("NoPrompt" = "red", "Morning + Noon" = "orange", "Morning + Evening" =
"yellow", "Noon + Evening" = "pink")

# Plot the boxplot of stepcount data by daypart
ggplot(data = Data2, aes(x = DaypartGroup, y = StepCount, fill = DaypartGroupText)) +
 geom_boxplot(width = 0.5, outlier.shape = NA) +
 scale_fill_manual(values = my_colors2) +
 labs(x = "Group", y = "Step Count", title = "Step Count by Group") +
 theme_minimal() +
 theme(plot.title = element_text(size = 16, face = "bold"),
    axis.title = element_text(size = 14),
    axis.text = element_text(size = 12),
    legend.title = element_blank(),
    legend.text = element_text(size = 12),
```

```
panel.grid.major = element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),
panel.border = element_blank())
```

Appendix D – Informed consent

Informed Consent

On behalf of Ancora, third parties will collect your personal data, information on your fitness and collect, code, store and analyze your blood and urine samples.

Your personal data and samples will be used for the sole purpose of your participation in the personal health program and will not be provided to any other parties other than parties involved. Parties involved are the onboarding staff (including doctors), the staff assessing your fitness and the labs analyzing your urine, your blood parameters and your DNA. Only relevant Ancora staff will be involved in processing your personal data.

The samples provided to the labs will be coded in such a way that your name cannot be deducted by them. After a maximum period of 6 months your blood and urine samples will be destroyed. The third parties provide the analysis results to Ancora for inclusion in your personal health passport. Ancora has selected the third parties based on their competence and their adherence to local laws and regulations related to collection of personal data and human samples. Ancora contracts and audit programs are in place to ensure appropriate execution of the work by these third parties.

You always have the right to withdraw the given consent to process your personal data. Should you want your personal data to be discarded or your samples to be destroyed we will do so upon receipt of your written request.

Ancora may use anonymized data, this data can no longer be linked back to you, for the improvement and development of its products and/or services, both internally and/or in partnership with other health/science institutions.

Ancora values your privacy and takes great care in the protection and confidential processing of your personal data. Ancora adheres to the applicable laws and regulations regarding data protection (GDPR). You can read the full Privacy Policy here.

I understand and hereby authorize the use of my personal data for the above-mentioned purpose(s)