# Exploring Message Receptivity and Protocol Adherence in a Clinical Study: A Micro-Randomized Trial Protocol

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## ABSTRACT

**Background** Digital health studies increasingly combine passive sensing with active self-reports like ecological momentary assessments (EMAs). However, adherence to active data collection often declines over time, affecting data quality. Reminder messages using personalization or loss-aversion principles may improve adherence, but their relative effects and optimal timing remain unclear. This micro-randomized trial (MRT), embedded in the *Glow Up* prediabetes detection study, examines message receptivity and adherence to EMA protocols.

**Objective** To examine how notification content (state-adapted, loss-aversion, or neutral) and physiological factors influence adherence to nutritional tracking in an observational study, aiming to inform future notification strategies.

**Methods** This MRT within the Glow Up study evaluates adherence to an EMA protocol administered to 200 participants over a 4-week period via a smartphone app. Participants will be randomized three times daily to receive one of three reminder conditions: state-adapted, loss-aversion, or neutral. The measured proximal outcome is survey completion, indicating protocol adherence. Additionally, data captured by wearable devices is analyzed to explore associations between physiological factors and momentary states of receptivity.

**Results** A 14-day pilot study with 20 participants in June 2025 will refine procedures. Main data collection begins in September 2025. Interim analyses will be conducted after 20% completion.

## CCS CONCEPTS

**• Human-centered computing → Human computer interaction (HCI) → Empirical studies in HCI**

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## KEYWORDS

micro-randomized trial, interactive systems, digital health, receptivity, adherence, loss aversion, context-aware computing

## 1 Introduction

The rise of commercially available wearable devices has expanded longitudinal health data collection opportunities, particularly in eHealth research [2, 18]. These devices provide passive data streams that enable the study of non-communicable diseases over extended periods of time with minimal participant burden. However, key contextual factors such as mood and nutrition logging still require active input, typically collected through ecological momentary assessments (EMAs).

EMA completion in clinical and digital health studies remains a challenge, particularly in studies requiring consistent self-monitoring, such as diet and nutrition tracking [5], as participant adherence often declines over time, with most participants engaging only sporadically after the initial days of a study [2, 6]. Low adherence compromises data quality and undermines the validity of findings, especially in biomarker studies where continuous data availability is critical [4, 16]. Despite efforts to increase patient engagement, this issue remains remarkably relevant to interactive systems for clinical research, where reliable data collection and data completeness are essential.

Prior research has established that well-timed and personalized reminders, alongside monetary incentives, can enhance adherence in digital health studies [2, 6, 12]. In this study, we explore these three mechanisms by directly implementing a state-adapted (personalized) and a financial loss-aversion based adherence intervention, followed by retrospectively analyzing optimal message timing.

In addition to offering adherence-contingent financial incentives of up to 3.3 CHF/day for all participants, we investigate how

reminders evoking loss-aversion [8] — a cognitive bias where individuals prefer avoiding losses over acquiring equivalent gains—improve adherence beyond the incentive itself. Loss-aversion has been found to serve as a powerful motivator, even when financial stakes are small [3, 17], and has been effective in increasing short-term adherence to eHealth nutrition tracking and EMAs [1, 7]. However, its effect diminishes over time, and prior studies lack long-term effectiveness and generalizability [1, 7]. By contrast, this study provides financial incentives to all participants and examines whether explicit reminders of financial loss improve adherence beyond silent loss enforcement.

Furthermore, while personalization is known to improve adherence to digital health tools, its definition remains ambiguous, particularly regarding which personal variables should guide it [15, 22]. Though physiological and mental states like stress or fatigue influence receptivity to reminders [9, 11], research on message framing for these states is limited. Evidence suggests that messages congruent with participants' affective state reduce processing effort by reinforcing expectations and enabling heuristic processing [23], yet it remains unclear whether aligning reminders with participants' states — especially when they may pose adherence barriers like low energy levels — enhances receptivity. This study implements personalization by constructing state-adapted reminders aligned with participants' current activity and energy levels.

Lastly, the concept of well-timed reminders remains under-defined. While prior research has explored receptivity using passive sensing [14], it has primarily relied on mobile phone data (e.g., accelerometer, geolocation, device interaction, battery level) [11, 14, 16], rather than psychophysiological measures which may reflect current cognitive capacity and thus receptivity to notification messages [9, 13]. While reminder timing is not adapted to psychophysiological measures in this study, a time-randomized delivery will allow for retrospective analysis of physiological signals which may be used to predict states of receptivity to reminders.

Our study addresses these gaps by investigating how reminder content and framing (state-adapted vs loss-aversion) affect participant adherence to image-based food tracking and EMAs in *Glow Up*, an observational study for prediabetes detection. Ideal message timing and participants' states of receptivity will be explored by retrospectively combining participant responsiveness to messages with physiological data to establish ideal contexts in which to remind participants of the study protocol tasks and provide actionable insights into improving adherence strategies for digital health studies.

### 1.3 Research Goals and Questions

We aim to assess the effectiveness of theory-driven reminder strategies to increase participant adherence to nutritional logging and EMAs by examining the timing and content of reminder notifications. Specifically, we aim to determine which contextual or physiological factors affect states of receptivity, whether state-adapted or loss-aversion framing enhances protocol adherence, and how these effects interact and evolve over time by addressing the following research questions: (1) How do state-adapted and loss-aversion reminder strategies compare and interact in their effectiveness at promoting adherence, and does this effect change over time? (2) How do participants' physiological and contextual states, as collected through passive sensing, influence their receptivity to different reminder strategies, and what are the interaction effects between physiological factors and message content on participant responsiveness?

## 2 Methods

### 2.1 Micro-Randomized Trials

An MRT is a study design that sequentially randomizes interventions over time to assess their impact under varying conditions [10, 19]. By delivering randomized reminder messages at each decision point, the design allows for assessing both state-adapted and loss-aversion strategies over time, capturing their causal effects on an outcome behavior [19]. MRTs also reveal state-dependent effects, intra- and inter-person variations, and whether the intervention effectiveness declines over time due to habituation [21].

### 2.2 Study Setting

The *Glow Up* study is a 4-week observational digital biomarker study using wrist-worn wearable devices and continuous glucose monitors (CGMs) to develop a prediabetes detection biomarker. Fitbit wearable devices will be used for passive sensing, while participants will engage in image-based nutrition tracking and short EMAs via a smartphone app three times daily.

*MyDataHelps* [25], a mobile application for clinical studies, will be used for participants to interact with and complete all required nutrition surveys. It provides a platform for synchronizing and consolidating participants' CGM and Fitbit data streams, survey data, and image-based nutritional logging. All surveys and onboarding questionnaires will be completed through this study app, which is available freely on the AppStore and GooglePlay. The informed consent process for *Glow Up* includes informed consent to data sharing through *MyDataHelps* and participation in the MRT.

### 2.3 Participants

Individuals are eligible to participate in *Glow Up* if they are Swiss citizens or permanent residents, at least 45 years old, have a BMI over 25 kg/m², can provide informed consent, read German, use a smartphone, and walk unassisted. Exclusion criteria include

unwillingness to wear a wearable device for the full study period or medical conditions contraindicating participation, as defined in the *Glow Up* clinical trial protocol.

## 2.4 Nutrition Logs and EMAs

During onboarding, participants will specify 1-hour windows during which they typically eat breakfast, lunch, and dinner. Meal tracking is expected within these times but remains participant-triggered. When starting a meal survey, participants will be prompted to capture an image or manually log their meal with a brief description and optional calorie/macronutrient input. The app requests location access to link meals to geolocation. Breakfast and lunch meal surveys collect no additional data to minimize participant burden. Dinner surveys include two follow-up questions assessing overall daily mood and perceived stress via sliding scales.

## 2.5 Randomization and Data Collection

Each meal serves as a decision point in the MRT. Within the 1-hour mealtime interval indicated by a participant at onboarding, the study platform randomly selects a time to trigger the MRT workflow (Figure 1). If the participant already logged the meal that day, no reminder is sent to minimize message fatigue. Otherwise, they are randomized with equal probability (0.33) to receive one of three adherence interventions: loss-aversion, state-adapted, or neutral messaging. A positive proximal outcome is completion of the meal survey within two hours of receiving a notification.

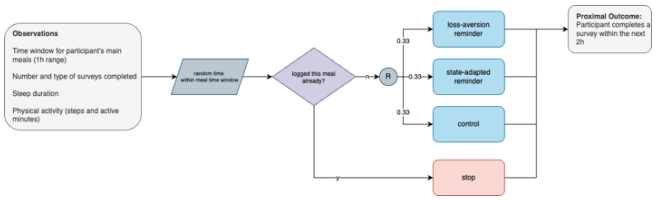


**Figure 1: MRT randomization and messaging flowchart**

Through the study platform, the following data is collected for analysis: (1) survey type (breakfast, lunch, dinner), (2) timestamp and type of notification, (3) timestamp of survey completion, (4) CGM data, (5) Fitbit data: HR, HRV, step count, active minutes, calories burned, sleep duration (6) location when meal tracking. Randomizing message content allows insights into which reminder content participants respond to most, the magnitude of these effects, and potential habituation effects over time. By randomizing message timing and analyzing survey completion alongside physiological and contextual data, the study allows for retrospective analysis of participants' states of receptivity, identifying patterns that indicate optimal intervention timing.

## 2.6 Adherence Intervention

A message bank is constructed for each of the three message types to avoid overly repetitive notification content. Message banks for all reminder types are created with the help of a large language model, where each message is reviewed by the research team before inclusion in the study.

*2.5.1 Control messages* For control reminders, a bank of 30 simple and neutral messages (e.g., *Please track your nutrition today.)* are constructed.

*2.5.2 Loss-aversion reminders* All participants receive financial incentives contingent on the proportion of meal surveys they complete. To qualify for daily remuneration, at least two out of three surveys must be completed on a given day. Reminders of the loss-aversion type will emphasize the financial loss incurred by not completing meal surveys. A financial loss-aversion reminder is sent if, at the time of randomization, fewer than two surveys have been completed on that day. If two daily surveys are already completed at randomization time, the reminder instead warns of losing a daily streak. Table 1 shows example messages for both cases.

**Table 1: Examples of loss-aversion messages**

| 0 or 1 surveys completed | 2 surveys complete |
|---|---|
| "Don't miss out on your daily reward! Take a minute to complete your [breakfast \| lunch \| dinner] survey!" | "⅔ done today, don't lose your streak! Make sure to log your dinner!" |

*2.5.3 State-adapted reminders* Fitbit integration with the study app provides real-time feedback on participants' physiological state to the randomization platform, enabling immediate state-adaption of messages. Message adaptation is driven by two key metrics: physical activity (measured by steps taken and active minutes), and sleep duration. Breakfast reminders are adapted based on sleep duration only, whereas lunch and dinner reminders also consider physical activity.

**Table 2: Examples of state-adapted lunch/dinner messages**

| Active | Sleep | Lunch/Dinner |
|---|---|---|
| No | High | "A relaxed day calls for an easy win - log your [lunch \| dinner] now." |
| No | Low | "It looks like today's a quieter day after a rather short night. Please remember to log your [lunch \| dinner] today." |
| Yes | High | "You've been on the move today - keep the momentum going by logging your [lunch \| dinner]!" |
| Yes | Low | "On a demanding day, we know you might be tired. No rush, but please log your [lunch \| dinner] when you have a moment." |

A day is classified as active if a participant exceeds 7,499 steps [20], or logs more than 30 minutes of physical activity [24]. Sleep is classified as low if the previous night's sleep fell more than one hour below a participant's self-reported baseline average; otherwise, it is considered normal/high. This results in a total of

two state-adapted conditions for breakfast reminders (high or low sleep), and four conditions for lunch/dinner reminders (combinations of high/low sleep and active/non-active day). A separate message bank is created for each combination. Table 2 shows example messages for reminders for all combinations of state variables.

## 3 Discussion

The main challenges in this study are dropout and technical problems. Dropout, where patients stop data collection or opt out, could impact statistical power despite already accounting for 20% attrition in our sample size calculations. To address this, we will proactively contact participants after 36 hours of inactivity. To mitigate technical issues, a 2-week pilot study will identify problems early, and participants will receive troubleshooting guides, detailed onboarding instructions, and ongoing technical support. By systematically evaluating states of receptivity and the effectiveness of theory-driven loss-aversion versus state-adapted reminders, this study will contribute actionable insights for improving adherence strategies to digital health data collection. The findings will help refine reminder timing and inform the design of adaptive digital health tools, with potential to contribute to more effective, data-driven behavioral health strategies.

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# Exploring Message Receptivity and Protocol Adherence in a Clinical Study

## Protocol for a Micro-Randomized Trial

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## 1. Problem

Digital health studies increasingly combine passive sensing with active participant self-reports (EMAs).

However**, adherence** to active data collection often **declines over time**, impacting data quality[1, 2].

This trial explores how **notification content**[3,4], **timing**[5], and **physiological factors**[6] impact **momentary message receptivity** and **adherence** to a digital health data collection protocols in the *GlowUp* pre-diabetes detection study.

## 2. Objectives

1. Assess how **message content** influences **adherence** to the study protocol (app-based EMA completion and nutritional tracking).
2. Explore how **physiological and lifestyle factors** relate to participants' **receptivity** to reminder messages.

## 3. Method

### Setup & Data Collection

**200 participants**
> 45 years
BMI over 25 kg/m²

**4 weeks**
3x/day nutrional log & EMA
wearable fitness tracker
glucose measurement

**adherence - contingent financial incentive**

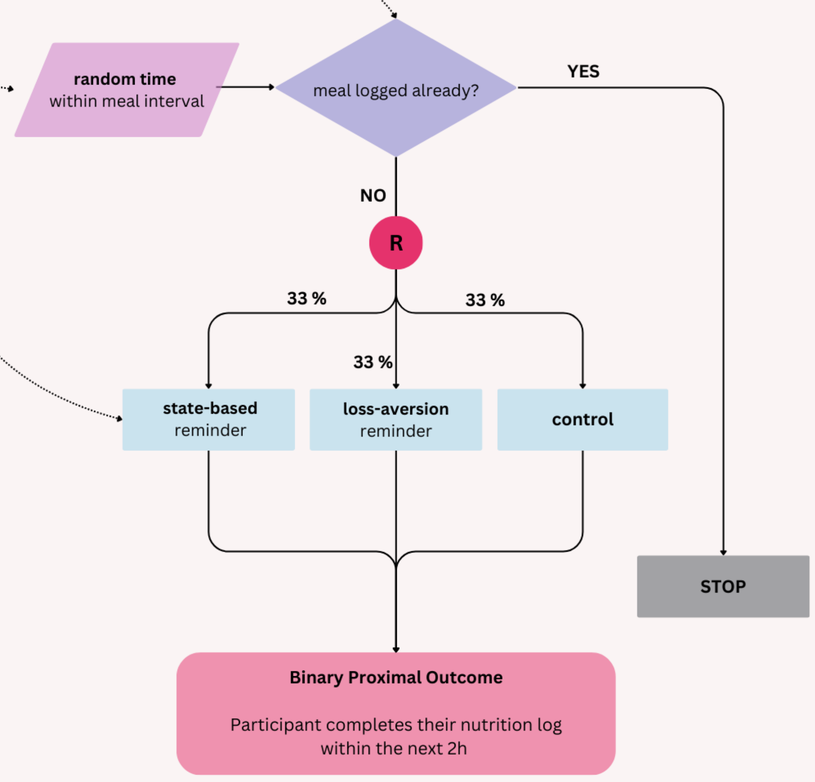
**number** and **type** of completed logs

**typical meal times** (1h intervals)

**sleep duration**

**physical activity** (steps, workouts)

### Micro-Randomization




### Message Conditions

You've been on the move today! Keep the momentum going by logging your lunch!

You had a very demanding day. No rush, but please log your dinner when you have a moment.

**state-based** reminder

**loss-aversion** reminder

Don't miss out on your daily reward! Take a minute to complete your lunch survey!

### Data Analysis

**1 Effects of Notification Content on Adherence**

MRT data allows estimation of **within-person** and **between-person causal effects**

Statistically assess **main effects** and **interactions** between message conditions

Analyze **temporal patterns** (e.g., effect fatigue or time-of-day moderation)

Evaluate **sequences of messages**

**2 States of Receptivity**

**Time series analyses:** Model how physiological signals and context predict receptivity

**Signals:** heart rate, HRV, activity, sleep, skin temperature, glucose, and self-reported mood/stress

## 4. Results

A 14-day pilot study will be conducted in June 2025 to refine study procedures and inform the final study protocol. The main study will recruit **200 participants** and is expected to start data collection in **September 2025**.

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