Exploring the Impact of Framing Styles in Behavior Change Interventions on Health Outcomes and User Engagement

Thalia Viranda
Cornell Tech
New York, NY,
tv74@cornell.edu

Zhiduo Xie
Cornell Tech
New York, NY,
zx324@cornell.edu

Melissa Tan
Cornell Tech
New York, NY,
mrt96@cornell.edu

Abstract

This study examines the impact of different framing styles in physical activity interventions—comparing "active" versus "sedentary" prompts—on physical activity levels and user engagement. Using data from the HeartStepsV1 randomized controlled trial, we will assess how these framing styles influence health outcomes as measured by step counts and time spent in activity, and user engagement, as measured by interaction count and minutes between notifications and the next detected physical activity. Additionally, we will explore the moderating effects of contextual factors, such as location and baseline self-efficacy. The findings will provide insights into optimizing behavior change interventions for physical activity.

1 Introduction

1.1 Background

Physical inactivity is a well-established risk factor for numerous adverse health outcomes, including both physical and mental conditions, as well as premature mortality (DeJong et al., 2003; Saunders et al., 2020; Katzmarzyk, 2023). Behavioral interventions aimed at increasing physical activity have demonstrated some efficacy; however, the impact of different framing styles—how physical activity recommendations are communicated to users—remains poorly understood. Prior studies suggest that subtle variations in how behavior change prompts are presented can significantly influence user behavior (Harr and Öhlund, 2023; Arshad et al., 2022). Despite this, few studies have directly compared the effectiveness of different framing strategies for interventions targeting physical activity improvement.

This study seeks to address this gap by evaluating the relative effectiveness of two distinct intervention framing styles: "active" framing, which emphasizes positive, energizing outcomes (e.g., “A 10-15 minute walk can boost your energy”), and "sedentary" framing, which highlights the consequences of inactivity (e.g., “Have you been sitting for a while? Take a 5-minute walking break”). Using data from the HeartStepsV1 study (Klasnja et al., 2019), a randomized controlled trial designed to promote walking through tailored prompts, we will assess how these framing styles influence (1) physical activity levels, measured by step counts and time spent in activity, and (2) user engagement, measured by response times to notifications.

Additionally, we will explore the moderating role of contextual factors, such as access to green spaces and individual differences in baseline self-efficacy, which have been associated with increased physical activity (Cardinali et al., 2024) and influence engagement in health-promoting behaviors (Rauff and Kumazawa, 2024). Our investigation is informed by the interdisciplinary expertise of our team, with a strong focus on healthcare innovation. We anticipate that our findings will provide critical insights into optimizing the design of physical activity interventions and offer guidance on when and for whom specific framing approaches are most effective.

1.2 Research Questions and Hypotheses

Our research questions (RQs) and hypotheses are as follows:

RQ1: How do "active" versus "sedentary" framings of activity suggestions compare in their impact on health outcomes, specifically steps taken and time spent in physical activity?

- H_{01}: There is no significant difference between "active" and "sedentary" framings of activity suggestions in terms of their impact on steps taken and time spent in physical activity.
- H_{a1}: "Active" and "sedentary" framings of activity suggestions lead to significantly different outcomes in terms of steps taken and time spent in physical activity.

RQ2: How do these two framing styles differ in their effect on user engagement, measured by the speed of response to activity prompts?

- H_{02}: There is no significant difference in user engagement, measured by response time to activity prompts, between the "active" and "sedentary" framing styles.
- H_{a2}: There is a significant difference in user engagement, measured by response time to activity prompts, between the "active" and "sedentary" framing styles.

Exploratory RQ: How do contextual factors, such as user location and baseline self-efficacy, moderate the impact of these framing styles on health outcomes and user engagement?

- H_{03}: User location and baseline self-efficacy do not significantly moderate the effect of "active" versus "sedentary" framing styles on health outcomes or user engagement.
- H_{a3}: User location and baseline self-efficacy significantly moderate the effect of "active" versus "sedentary" framing styles on health outcomes and user engagement.

2 Methods

2.1 Dataset Description

We will utilize data from the HeartStepsV1 study, a mobile health (mHealth) intervention designed to promote regular physical activity by delivering walking suggestions tailored to individuals' current context. The dataset was collected during a six-week micro-randomized trial, involving 37 participants. Each participant could receive up to five contextually tailored activity suggestions per day, delivered at personalized times. These notifications encouraged participants to engage in physical activity based on their current situation, including their physical activity levels and environmental context.

2.2 Planned Data Science Workflow: Alignment with the PCS Framework

Data cleaning and pre-processing We will handle missing or inconsistent data using multiple imputation and ensure standardized units across all variables, particularly step counts and time measurements. Step data from both Jawbone and Google Fit will be cleaned to remove outliers and errors. New variables will be generated for framing type ("active" vs. "sedentary") and engagement time, calculated as the time between notification and subsequent physical activity. Demographic data will be summarized, and self-efficacy scores computed. Finally, we will prioritize one physical activity dataset for analysis, with the other used for stability testing to ensure robustness.

Exploratory Data Analysis We will summarize key metrics, including average steps, active minutes, interaction counts, and the time between notifications and subsequent physical activity. Visualizations will compare the effects of "active" vs. "sedentary" framing and explore correlations between self-efficacy and activity outcomes. We will also identify and address any patterns or anomalies, such as outliers, that may affect the data.

Statistical Analyses Plan In this study, we will employ inferential analytical approach to evaluate the effects of different framing styles ("active" vs. "sedentary") on health outcomes (e.g., step counts, time spent in physical activity) and user engagement (e.g., response times to activity prompts). Our analysis will be structured to address the primary research questions as follows.

To directly test the effects of framing style, we will conduct inferential statistical analyses to determine whether the "active" and "sedentary" framing lead to significantly different health outcomes and user engagement. Mixed-effects models will be employed to account for the repeated measures structure of the data, as participants receive multiple suggestions over time. The primary fixed effect will be the framing style, while random intercepts will model individual variability. Covariates such as location and self-efficacy will be included as moderators to test for interaction effects, providing insights into the contextual factors that influence framing effectiveness. Hypothesis testing will be conducted using significance levels (e.g., $p < 0.05$), and confidence intervals will be reported alongside effect sizes.

For the exploratory research question, we will perform interaction analyses to examine how contextual factors (e.g., location at the time of notification) and personal characteristics (e.g., baseline self-efficacy) moderate the effect of framing style on health outcomes and engagement. This will involve including interaction terms in the inferential models to assess whether these factors significantly alter the impact of framing styles.

Evaluation of Results To determine which framing style ("active" vs. "sedentary") significantly improves health outcomes and user engagement, we will employ a combination of statistical analyses and model validation techniques. Mixed-effects models will be used to evaluate the effect of each framing style on key outcomes, such as step counts, time spent in physical activity, interaction count, and minutes between notifications and the next detected physical activity.

To ensure the robustness and generalizability of the results, we will validate our findings through cross-validation. This will involve applying the models to an alternative physical activity dataset, as well as testing performance across different data subsets, such as user demographics (e.g., socioeconomic status), which may influence mobility patterns and engagement levels. This approach will allow us to assess the stability of the model and its capacity to generalize across varying data conditions and user characteristics, ensuring the reliability and applicability of our conclusions.

Communication of Results We will create clear and accessible visualizations to effectively communicate our findings. A comprehensive summary will be prepared, tailored to both academic researchers and a broader, non-expert audience. The results will be disseminated through a midterm paper, presentation, and made publicly available via a GitHub repository.

Bias Mitigation Plan To address potential biases from incomplete or inaccurate data from the Jawbone Tracker or Google Fit, we will conduct thorough data cleaning, flagging inconsistencies and using multiple imputation for missing data. Sensitivity analyses will be performed to assess the impact of measurement errors. Additionally, potential confounding variables such as user location, self-efficacy, and baseline physical activity will be controlled for in regression models, with stratified analyses used to isolate their influence on the relationship between framing and outcomes.

2.3 Work Plan

In this project, we will split the tasks as follows:

- **Thalia**: Focus on Exploratory Data Analysis tasks, inferential analysis, and leading the evaluation of results. Thalia will also contribute to communication of results.
- **Melissa**: Handle the majority of data cleaning and preprocessing tasks, managing missing data, standardizing formats, and preparing variables, and will lead the communication of results by creating visualizations and summary reports.
- **Zhiduo**: Assist in data cleaning and pre-processing tasks and contribute equally to the inferential analysis and the evaluation of results. Zhiduo will also contribute to communication of results.

Project Github Repository This project's drafted github repository can be found here

```
ORIE-5160-midterm-project/
│
├── data/
│   ├── gfsteps.csv          # Google Fit step data
│   ├── jbsteps.csv          # Jawbone tracker step data
│   ├── suggestions.csv      # Activity suggestions and context data
│   └── users.csv            # User demographics and survey data
│
├── dslc_documentation/
│
├── functions/
│   ├── 01_cleaning.ipynb    # Data cleaning script
│   └── 02_eda.ipynb         # Exploratory Data Analysis script
│
└── README.md
```

Figure 1: The Project's Repository Structure

Results

(To be filled).

Discussion

(To be filled).

Conclusion and Limitations

(To be filled).

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