The Impact of a "Well-Timed" Nudge on Individual Physical Activity and Health Outcomes Via Wearable Devices

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1. Introduction

The prevalence of obesity and sedentary lifestyles has increased significantly in recent years, leading to numerous health problems, particularly in the United States. Studies have shown self-monitoring, via a wearable device, can modify health behaviors, including physical activity (PA) (Alturuki and Gay, 2016 and McDonough et al., 2021). Additional studies have shown that digital nudges are effective in influencing human behavior (Sobolev, 2022 and Mele et al., 2020). With wearable devices such as the Apple Watch and Oura Ring gaining popularity and being advertised as effective tools to improve physical activity, our goal is to investigate if these devices are being used to their full potential.

This study aims to examine the effectiveness of a well-timed nudge that appears on a wearable device to promote physical activity and, as a result, improve health outcomes. Specifically, the study will focus on the impact of the nudge on resting heart rate, daily number of steps, and minutes of increased daily physical activity obtained from the wearable device. We will use a randomized control trial in the student population of the State University of New York (SUNY), which has 64 unique campuses – from urban to rural, and small to large – in an attempt to make the study nationally representative. There is currently little research on how a nudge via a wearable device impacts PA and health outcomes. We will randomize an intervention of a digital nudge focused on meeting a minimum standard of daily physical activity. We will study the direct impact of these interventions on baseline resting heart rate, baseline daily number of steps and baseline weekly active minutes.

2. Motivation and Conceptual Framework

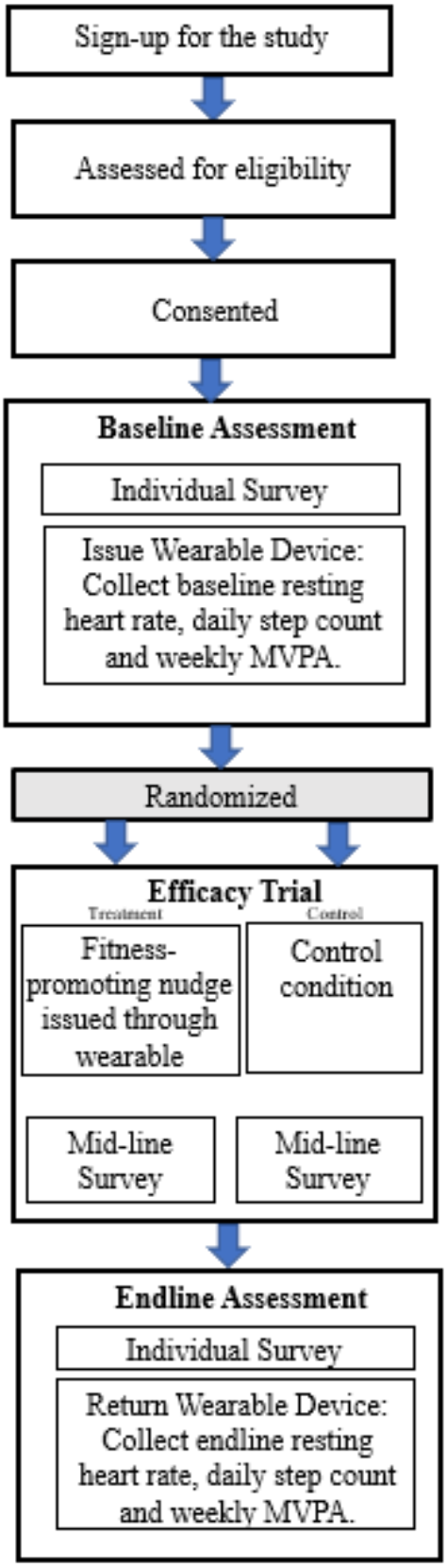
2.1 Motivation

Americans continue to experience an array of obesity-related health issues such as diabetes, and heart disease (CDC, 2020), in part due to factors such as poor nutrition and low physical activity (Roglic, 2016). Health ailments negatively impact not only individuals and their families but society at large, carrying financial burdens for agents such as employers and health insurance companies (Carlson et al., 2015; Jardim et al., 2019). Over one third of American adults are obese and less than half do not meet weekly recommended levels of moderate- to vigorous-intensity PA (MVPA) (150 minutes). With this in mind, it is a public health priority to develop low-cost interventions to increase PA levels.

2.2 Conceptual Framework

The conceptual framework for this study is based on the behavioral economics concept of nudging, which suggests that small, subtle changes in the environment can influence behavior (Zey, 2022). The well-timed nudge on a wearable device is a potential intervention that can encourage physical activity and improve health outcomes.

Figure 1. Study Design


Sign-up for the study
Assessed for eligibility
Consented
Baseline Assessment
Individual Survey
Issue Wearable Device: Collect baseline resting heart rate, daily step count and weekly MVPA.
Randomized
Efficacy Trial
Treatment
Control
Fitness-promoting nudge issued through wearable
Control condition
Mid-line Survey
Mid-line Survey
Endline Assessment
Individual Survey
Return Wearable Device: Collect endline resting heart rate, daily step count and weekly MVPA.

3. Samples and Intervention

3.1 Samples

Our experiment will take place within the student population of the State University of New York (SUNY). The 64 campuses of SUNY are in urban and rural areas of New York. College students are a convenient and accessible population for researchers to study. This can help to increase the generalizability of the findings, as college students are often seen as a representative sample of young adults in general. To recruit participation in our study from this population, we will place paper advertisements in common areas throughout the campuses, send digital flyers via student emails and advertise on the school website and through social media. Students will be compensated at $20/hr for travel time and while students are with a medical professional during the baseline visit and over the phone during the midline survey. Furthermore, participants will be compensated at $40/hr for the endpoint visit in an effort to minimize attrition. Compensation will be delivered at the endpoint visit, and non-compliance will result in no compensation. Additionally, students will be able to keep their wearable, or receive a cash payout for the equivalent value of the used wearable.

To be eligible to participate, students must be between the ages of 18 and 25. Limiting the age of participants has several advantages. By limiting the age range of participants, we can create a more homogeneous sample. This can help to reduce variability in the data and increase the statistical power of the study. Additionally, young adults between the ages of 18 and 25 are in a unique developmental stage, characterized by significant changes in their social, emotional, and cognitive development. Focusing on this age range can help us to better understand how behaviors and habits are formed and how they can be modified. Focusing on young adults in this age range can have significant public health implications. This age group is at risk for developing sedentary lifestyles and poor health habits, which can have long-term consequences for their health and well-being. Finally, limiting the age range of participants to adults over 18 helps to ensure that participants are legally able to provide informed consent and make their own decisions about participating in the study (Wang et al., 2015).

Our sample size will be relatively large (N>500), and will be stratified based on key demographic characteristics and prior experience with wearable devices. Individuals that are noncompliant with the study will be dropped from the dataset, and will not receive compensation. Noncompliance is measured on a daily basis for all study participants. Participants not wearing the device for longer than 90% of their waking hours will be excluded from the daily sample. Participants with noncompliant days greater than 90% of the study period will be excluded from the study.

3.2 Intervention

In our experiment, we will evaluate the impacts of customized timed nudges based on machine learning (ML) models stemming from daily data collection: individuals assigned to this intervention will receive a notification customized to each individual's personal physical activity patterns. For example, the wearable device could track an individual's daily activity levels, such

as the number of steps taken, or the amount of time spent exercising. Based on this data, the machine learning algorithm will generate personalized nudges to encourage the participant to engage in physical activity. The ML model will be constructed using a Thompson Sampling model (Russo, et al. 2018). Thompson sampling is particularly useful for nudge based experiments as it balances exploiting prior data to maximize return with testing alternative inputs (e.g. timeframes) to produce positive results.

3.3 Randomization

We will randomize the ML nudge intervention at the level of the individual. We will assign 20% of the sample (about 100 individuals) to pure control (no nudge of any kind) and 80% to receive the ML nudge (about 400 individuals). This division of the sample is motivated by the various subanalyses we aim to conduct to better understand the impact of the intervention on different populations. Thus, these subanalyses require a larger sample size to be sufficiently statistically powered.

To make the study nationally representative, we will use stratified random sampling. Stratified random sampling is a type of sampling method used in research that involves dividing the population into subgroups or strata based on key characteristics that can help account for endogenous factors and improve the precision of the research (Vajravelu and Silva, 2021). In the context of this study, stratified random sampling can be used to ensure that the sample is nationally representative of the United States racial demographics by dividing the population into subgroups based on race, gender, and ethnicity and then selecting a random sample from each subgroup.

Once the strata are identified – based on the most recent data from the U.S. Census Bureau – we will randomly select participants from each stratum to ensure that the sample proportionally represents the different groups in the population.

3.4 Risks

The risks associated with this study are minimal, as the intervention is a well-timed nudge on a wearable device. Our project will be reviewed by the American Public Health Association (APHA), the Association for Behavior Analysis International (ABAI), and the National Institutes of Health (NIH). The data collection involves no more risk than a participant is already used to as a regular wearable user (ie. discomfort or irritation from prolonged periods of wearing the device). Some participants will be randomly selected to receive a fitness-focused nudge from their wearable device, but all participants will wear the wearable device.

One concern would be that the individual may potentially sell the device that they are issued. This will be mitigated through each participant signing a contract that holds them financially liable for the full cost of the wearable device should they fail to complete the exit procedure for the study. Further, compensation will be tied to completion of the exit survey as well. Only data from those who were issued and returned the device at the endline assessment will be used in the study.

Additional concerns include biases associated with voluntary participation. Self-selection bias is where individuals who choose to participate in the study may have different characteristics or

motivations than those who do not. This can lead to biased results, where the study participants are not representative of the larger population (Tang et al., 2020). Response bias may also be an issue. Even among those who choose to participate, some may be more likely to respond to certain questions or in certain ways than others. This can lead to inaccurate or incomplete data (Jin et al., 2020).

These bias limitations will be mitigated in several ways. First, our study will have a large sample size (N>500). This can help to increase the representativeness of the sample and improve the statistical power of the study. Second, we will conduct stratified random sampling in an effort to construct similar control and treatment groups, mitigating sources of bias that may arise from inter-group characteristics. Finally, we will use multiple recruitment methods to reach a diverse group of participants. For example, we will recruit participants from different locations, use social media and online platforms to reach a wider audience, and partner with community and campus organizations to increase participation among underrepresented groups.

All adults will consent to participate via written agreement outlining all relevant study details prior to the start of the research. All data will be anonymized to avoid potential risks of data privacy breaches. Individuals will also be free to withdraw from the study at any point or not to answer any questions during the interviews.

3.5 Data Sources

We plan to collect data from individuals continuously over the academic year (i.e., a 9-month period) and will administer surveys at three points in time: at baseline (upon issuance of the wearable device), four months after baseline (midline), and 9 months after baseline upon return of the wearable device (endline), which coincides with the end of the academic year. The continuous data will be passively collected and obtained through the wearable. This data will include resting heart rate, daily number of steps and weekly MVPA. These data will help determine if there are significant changes in health outcomes. The baseline survey will collect information about the individual's previous wearable use, eating habits, exercise habits, sleeping habits, alcohol and tobacco use, stress levels, and demographic information. The midline survey, six to seven months after baseline, will be a shorter survey focused on any changes (improvements or deteriorations) to baseline the individual noticed. The endline will measure the same outcomes as baseline. The continuous data collected over the 9 month period will be plotted over time and the baseline data from the first month will also be compared to the endline data from the 9th month to determine if there was significant change. The baseline and endline surveys will be face-to-face, tablet-based interviews. The midline will be administered over the phone.

3.6 Timeline

The study will take place over a year, with participants wearing the device throughout the study period. Data will be collected at regular intervals throughout the study period, and the final analysis will be conducted at the end of the study.

• Baseline surveys of participants (Start of survey)

• Implementation of intervention (Two weeks)

• Midline survey of participants (Month 4)

• Endline survey of participants (Month 9)

4. Outcomes and Hypotheses

The wearable device, baseline and endpoint assessments, and survey will be used to measure the impact of wearables and the nudge intervention on participant health. Specifically, four primary outcomes will be measured to understand the effect of the two conditions on participant behavior:

a. The degree to which one engages in MVPA.
b. Changes in resting heart rate.
c. Average daily number of steps.
d. Changes in BMI.
e. Participant perception of the messaging on motivating healthy behavior.

Each of these dimensions in addition to relevant control variables are discussed in greater detail below.

Wearables:

- Wearables assigned to both the ML and control groups will record the following three variables: (a) Moderate to Vigorous Physical Activity (MVPA), (b) Resting Heart Rate, and (c) Average daily number of steps. These real-time measures will be recorded every day for each participant.
    - Moderate to Vigorous Physical Activity (MVPA): This will be a continuous variable indicating the number of minutes a participant engages in moderate to vigorous physical activity each day. "Moderate" and "vigorous" intensity will be measured at the following thresholds suggested by the CDC: a heart rate between 64%-76% and 77%-93% of one's maximum heart rate, respectively (CDC, 2011). Maximum age-related heart rate is measured by subtracting one's age from 220. Participants in the ML condition will receive messages encouraging them to engage in MVPA at optimal moments throughout each day. When data are analyzed, the amount of time following each message that a participant engages in MVPA (if they engage in MVPA) will be studied to understand the efficacy of the intervention. The control group will receive no such messaging.
    - Resting Heart rate: This will be measured as a continuous variable indicating a participant's average daily resting heart rate. Generally, a resting heart rate within a healthy range (60-100 bpm) suggests that one's heart is more efficiently pumping blood around the body. When comparing groups, the percentage of participants within the healthy range during baseline/endpoint will be compared.
    - Steps: The average daily number of steps will be recorded as another method to understand a participant's engagement with PA (in addition to studying MVPA). This will be recorded as a continuous variable indicating the average number of steps a participant takes on a given day. Participants in the ML condition will be prompted with well-timed messages, encouraging them to engage in lower levels

of activity throughout each day (in addition to higher levels of PA). For example, they will be encouraged to take the stairs instead of the elevator whenever possible, or to walk to class instead of using a motorized scooter. The control group will receive no such messaging.

Baseline and endpoint measures:

- Participant vitals (pulse rate and blood pressure), demographics, and clinical characteristics (diabetes, hypertension, dyslipidemia, heart issues, and substance usage), will be recorded by a medical professional during baseline and endpoint. These measures will be used to better understand the potential impact of the wearables through cross validating variables, subgroup analyses, and while controlling for various relevant characteristics.
    - **Vitals**:
        - Heart rate: This will be a continuous variable indicating a participant's heart rate. This will be cross validated with the participant's wearable to ensure the device is operating correctly. Additionally, this measure will be used as part of the primary outcome variables.
        - Blood pressure: this will be measured as a continuous variable and used to understand how one's blood pressure changes over the course of the study. Additionally, this variable will be used as a control variable in the final analysis, as it is a potential risk factor for various relevant health conditions (e.g., hypotension/hypertension and Addison's disease).
    - **Medical characteristics:**
        - BMI: This will be a continuous variable calculated using a participant's height and weight. This variable will be used as a primary outcome variable with attention to changes between baseline and endpoint as well as what the CDC considers to be a healthy range (18.5-24.9) (CDC, 2022).
        - Sex (male/female): A dichotomous variable indicating the sex of the participant. This will help us both control for endogeneity related to sex as well as conduct sub-analyses.
        - Age: This will be measured as a continuous variable indicating the participant's age.
        - Health conditions: This will be a set of dichotomous variables for each health condition, indicating whether a participant experiences any relevant health conditions (e.g., diabetes, hypertension, Dyslipidemia, heart issues). Health conditions will be controlled for in the analysis of this study as they may bias the estimates of each condition on the primary outcome measures of interest.
        - Relevant substance use: This will be a set of dichotomous variables for specific substances used by participants (e.g., cigarettes and vapes). Controlling for participant substance use will help us address endogeneity concerns and better isolate the impact of wearables and nudges on various health outcomes. For example, given that nicotine increases blood pressure and heart rate, a participant who quits smoking cigarettes mid-

study may bias results such that the intervention (whether that be the control or ML condition) may appear to be more effective than in reality.
        - Race/ethnicity: This will be a categorical variable indicating a participant's race/ethnicity. This will help better understand how wearables may affect individuals of different backgrounds differently, motivating important future research.

Survey measures:

- The survey, which will be administered at three times throughout the study, will be used to (a) help identify mechanisms for behavioral and physiological outcomes, and (b) control for factors in our analysis that may bias our results. Many of the questions below will ask about one's experiences in the current week compared to the week prior. This approach aims to understand general trends in one's thoughts, behaviors, and experiences, while minimizing day-to-day variability across participants.
    - Question: "Overall, do you feel that the fitness-related messaging is encouraging you to engage in physical activity?"
        - This question will be measured as a dichotomous variable and help us understand the reception of the messaging (i.e., better isolate whether it is a mechanism for changes in exercise rates). Only participants in the treatment condition will receive this message.
    - The following questions will be measured as categorical variables and used as controls to help isolate the effect of one's PA on their health outcomes (e.g., BMI).
        - "Would you say you're eating habits are currently "healthy?"" (rate on a scale of 0-5 with zero being extremely unhealthy and 5 being extremely healthy).
        - "Would you say your eating habits this week have been healthier, less healthy, or the same degree of healthy compared to last week?"
        - "In the past week, on average, how many hours of sleep a night do you get?"
        - "Would you say your sleeping habits are healthier (e.g., 8-hours a night), less healthy, or the same degree of healthy compared to last week?"
        - "In the past week, how many days have you consumed alcoholic beverages?"
        - "On average, how many drinks do you consume in one sitting?"
        - "Would you say you're drinking more, less, or the same amount of alcohol this week compared to last?"
        - "Based on last week, have you smoked any cigarettes or used electronic smoking devices?"
        - "Would you say you smoked more, less, or the same number of cigarettes this week compared to last?"
        - "How would you rate your current stress level?" (rate on a scale of 0-5 with zero being completely unstressed and 5 being extremely stressed).
        - "How stressed are you this week compared to last? More, less, or the same?"

Primary hypotheses:

- The primary hypotheses in the current study compare outcomes between the ML and control conditions of the intervention. Specifically, given the outcome measures described above, we hypothesize that compared to the control, the ML group will have a:
    - Greater average number of MVPA sessions per week.
    - Increased percentage of participant in the healthy heart rate range (60-100).
    - Greater average number of daily steps.
    - Increased percentage of participant in the healthy BMI range (18.5-24.9).
- To better understand the causal impact of the messaging, we hypothesize that there will be a positive correlation between those who feel the messaging helped and the various measures listed above (i.e., MVPA, heart rate, steps, and BMI).

5. Estimation Methodology

5.1 Measurement and Model Design

The study will use a multi-arm experimental design, with single-blind assignment to treatment and control groups, with surveyors blind to treatment allocation. Broadly, the sample will be divided into two categories:

- 20 percent of the sample will be assigned to the control group, where participants will not receive any nudges
- 80 percent of the sample will be assigned to the treatment group, where participants will receive nudges based on a ML model.

Stratified sampling will account for demographic representations, with an effort to align race, gender, and ethnicity variables in a representative manner.

The primary analysis of the data will be conducted through multiple fixed-effect regression models leveraging collected activity and health data as the dependent variable. Multiple regressions for the study are critical to determining the effectiveness of the intervention because measured outcomes (MPVA, resting heart rate, step count) provide sufficiently valuable health information independently. For example, if treatment is associated with an increased step-count but no change in MPVA or resting heart rate, it would suggest that the nudges were effective in inducing only low-difficulty exercise. A two-way (time and entity) fixed effect model is the best method for eliminating omitted-variable bias as it can control for time-varying factors associated with the messaging and our various outcome measures, and unchanging variables (e.g. demographics). Interaction terms will be used to evaluate treatment effect.

Figure 2: Model Specification

$$Yit = 0 + 1Tit + i + t + it + it$$

where *i* represents a participant index, *t* represents a time index, represents entity fixed effects, represents year fixed effects, represents all control variables, and is the error term.

5.2 Treatment Effect Heterogeneity

Beyond standard demographic subanalysis, there are a few sources of treatment effect heterogeneity that will be accounted for in the interpretation of the study results as well as the study design.

1. Prior use of wearable: We will measure the effect of the prior use of the wearable by comparing the behaviors of prior wearable users across the control and the treatment group. Our standard analysis concerning the efficacy of experimental nudges will be used to evaluate differential effects that may be induced by prior exposure to wearable devices. The experimental design will stratify those that used a wearable device prior to the experiment, and the entry survey will collect this data so it can be controlled for in our final analysis.
2. Asymmetric free time: The frequency of regular exercise may be impacted by both educational course load and extracurricular activities. In addition, the response to individual nudges is likely strongly influenced by environmental factors. For example, treatment participants will not be able to respond to a nudge if they are required to be seated for their work. While the ML model solves for some of this variability by conforming to student's behavioral patterns to optimize nudge efficacy, reports of hours of work and school schedule (e.g. number of credits and the area of study) could be taken to account for differences in the expected activity level. Entry, midpoint, and exit surveys will feature questions on available time to control for this effect.
3. Gym accessibility: The proximity of workout facilities to participant's place of residence will be considered when evaluating treatment efficacy. Nudges sent to an individual with a gym in their apartment complex will likely relieve more positive responses than those sent to a participant that must travel several miles to engage in exercise. Entry, midpoint, and exit surveys will feature questions on accessibility so this effect can be controlled for in our results.
4. Weather: Finally, weather conditions will be considered when evaluating the efficacy of nudges. Nudges ignored after a significant snowstorm, for example, may more accurately be attributed to weather conditions than the effectiveness of the nudge. Weather status will be retrieved from the location of the wearable at the time of the nudge, and at random intervals for the control group. Days that are below freezing or feature rain or snow will be coded as such. Weather data will be pulled from the national weather service for the GPS location of the wearable at the time of any nudge. Imputed data from the nudged weather analysis will be used for the control group when applicable. For deeper analysis on the impact of weather, collected data can be aggregated across participants in sufficiently similar locations over time.

5.3 Threats

Attrition: Attrition is an inherent risk with any longitudinal study. Participants benefit from the wearable itself, which helps mitigate the chance of attrition. Additionally, the compensation plan described in the samples section (3.1) should further reduce attrition risk. Regular follow ups with participants will help reduce attrition as well as catch cases where it has occurred at the midpoint and endpoint of the study. Research principles will take every effort to work with

participants' schedules to limit cases of attrition due to midpoint survey non-compliance whenever possible.

Resale and Transfer: Resale of an electronic device used in any study is an inherent risk. While the possibility of resale cannot be eliminated, researchers will inform study participants that the wearables are equipped with GPS tracking and that the exit survey must be conducted at the end of the testing period to receive test compensation. Combined, these safeguards should reduce the possibility that a study participant will sell the device. Transfer of the device is more plausible. Regular monitoring of location and health data can be used to determine participant compliance. Suspected non-compliant participants will be flagged for review by the research principals, and sufficient evidence supporting noncompliance will cause the participant to be dropped from the study.

Nonstandard Use: Use of the wearable in nonstandard manners may compromise passively collected data. Resting heart rate, for example, is often calculated as an individual wakes up or prepares to sleep. If a study participant leaves the wearable in the charger overnight, these measurements may include elevated activity from the individual moving to place the wearable on their wrist. Furthermore, if individuals are charging their device at different times during the day, wearables may fail to collect critical activity data. This threat to treatment data is difficult to control for, as wearables require sufficient battery life to collect comprehensive health data. Participants will be provided with 3 regularly scheduled time slots to recharge the wearable on a given day, but every effort to improve battery life and reduce the frequency of charging disruptions will be undertaken when selecting the wearable for study use.

Self-Selection Bias: Introduction into the sample requires students to respond to advertisements for the study. As a result, self-selection bias is an inherent concern for the study. Because we cannot require individuals to engage with the study, this bias should be considered when interpreting study results.

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