# Ameliorating Social Isolation in Populations Facing Health Disparities: Identifying Social Structural and Person-level Factors that Impede or Facilitate Health-related Social Behavior Change

## DATA ANALYSIS PLAN

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# AIM 2: TEST MAIN EFFECTS AND THEORY

Analyze main effects of the intervention on young adults' social isolation and loneliness and test theory-driven mechanisms by which health communication messages in the Keep Social RCT may affect social isolation and loneliness to identify intervention targets.

## ACTIVITY 2A: EVALUATE PRIMARY AND SECONDARY OUTCOMES OF THE KEEP SOCIAL RCT

### Pre-Processing and Models to Support Tests of Main Hypotheses:

**Pre-processing of Day Reports data:** We will omit the first week of Day Reports from our data analysis to remove the elevation bias commonly shown in repeated assessments of emotions and other internal states (Shrout et al., 2018).

**Pre-processing of GPS data (behavioral indicators of social opportunity and social isolation):** We will determine the best ways to assess and reduce the resulting geospatial data (coordinates with timestamps) prior to completing analyses. We intend to report results for multiple data reduction methods to allow researchers to learn from and advance these approaches because methods for reducing geolocation data to infer social opportunity and social isolation remain in development. The data clustering algorithm DBSCAN will be used to derive our measures and to identify location clusters. Following processing methods by Heller et al. (2020) and Reneau et al. (2024), we will also use raw coordinates.

We will assess the number of distinct locations visited per day and across the four-week intervention period, as well as roaming entropy (by closely following the code developed by Heller et al., 2020), which assesses the number of locations visited as well as the proportion of time spent in different locations. We also plan to assess time spent at home versus time spent in public places by identifying a "home" cluster, defined as the location most visited between 2am and 6am (when participants are likely to be sleeping).

**Pre-processing of behavioral motivational value data:** Our behavioral measure of motivational value (a.k.a., Implicit Motivational Value, or iMV) is estimated in a choice task as k values for stimulus types using a reinforcement learning (RL) paradigm and computational approaches as described in prior work by Waugh et al. (2023). The task stimuli include fractals that precede the presentation of headshot photos of unfamiliar others. Those photos show persons with one of 3 facial expressions: smiling-with-direct-gaze, smiling-with-gaze-averted, and neutral-with-gaze-averted. Participants are instructed to select their preferred fractal. k values are parameters of the MV, derived from standard Q learning models. We will take the median of participant's k values per stimulus type to create a single k value for each affordance type (i.e., smiling-with-direct-gaze, smiling-with-gaze-averted, and neutral-with-gaze-averted).

**Pre-processing of open-text social connection data:** We intend to use Natural Language Processing or similar analytic methods to infer individuals' levels of social connection from their open-ended narrative responses. To index social connection, we will use both top-down (theory-driven) dictionary-based approaches, specifically the Linguistic Inquiry Word Count (LIWC) and also bottom-up (data-driven) open-vocabulary linguistic features (words, phrases, and topics). LIWC scores represent the relative frequency of designated words within each LIWC category, ranging from 0.0 to 1.0. Higher scores represent greater frequency of the designated word category.

Latent Dirichlet Allocation modeling (LDA) will be used to generate "topics" that represent data-driven linguistic features. We will compute the topic distribution of each participant, ranging from 0.0 to 1.0. Higher scores represent greater frequency of the designated topic.

## Main Hypothesis Tests:

**Main effects for outcomes with repeated measures:** To test our hypothesis of main effects of experimental condition on **social opportunity or isolation (GPS), and self-reported loneliness (day and biweekly measures, which are assessed separately),** we will fit growth curves (e.g., longitudinal structural equation models (LSEM) and/or multilevel models) in two steps. This approach simultaneously models change over time within each individual and change patterns across individuals, facilitating unbiased significance testing. Missing data will be handled using full information maximum likelihood if the missing mechanism is MCAR (missing completely at random) or MAR (missing at random). First, we will plot each GPS variable (number of locations visited, roaming entropy, and left home) over time to create plots to identify patterns of change over 6 weeks. We predict one of two potential patterns. One possibility is that the scatter plots show linear growth or non-linear growth (e.g., quadratic growth). If so, we will then fit an unconditional growth model to estimate the slope and the intercept of social isolation across six weeks. The other possibility is that scatter plots show growth for a period and stay relatively unchanged after a certain timepoint (a spline model). In that case, we will fit a spline model (e.g., a latent piecewise linear growth curve model and/or spline multilevel model) to estimate the slope and the intercept of social isolation as well as the breakpoint at which changes plateau. Next, randomized condition will be indicator-coded and added as a separate predictor to compare the experimental condition to the control condition. A conditional growth model will next be fitted to test for condition differences. Second, we will repeat this approach with the remaining primary outcomes and secondary outcomes. Distinct from our GPS-based indicators of social opportunity and isolation, however, scores on all other outcomes come from the Day Reports or Biweekly Assessments. We will confirm our main hypothesis if the experimental health communication leads to higher scores on social opportunity / lower scores on social isolation (GPS), and lower self-reported loneliness (Day Reports and Biweekly Assessments) relative to the placebo control group.

For outcomes that were assessed at only two time points (e.g., alcohol use, psychologically rich life, which were assessed at BW2 and BW4), we will estimate a two-wave longitudinal structural equation model to test for intervention effects. Specifically, we will fit a model regressing the BW4 outcome variable on both the BW2 outcome variable and experimental condition (coded as a binary predictor). This approach provides an estimate of the intervention's effect on alcohol use at follow-up, adjusting for baseline alcohol use. If model fit is adequate, we will interpret the condition coefficient as the effect of the intervention, controlling for prior levels of alcohol use.

As with other models, missing data will be handled using full information maximum likelihood (FIML), assuming data are missing completely at random (MCAR) or missing at random (MAR).

**Main effects for outcomes assessed once:** For the outcomes that are assessed only once during the RCT (e.g., behavioral motivational value for strangers-smiling-with-direct-gaze, open-text social connection data extracted using natural language processing or similar methods, positive spontaneous thoughts), we will use a regression model to test for mean differences in outcomes by experimental condition.

## ACTIVITY 2B: TEST THE EFFECTS OF SPECIFIC MESSAGES

We will test the impact of specific messages from Invibe on social interaction behavior and examine whether effects of specific health communication can be explained through three mediators: perceived message effectiveness, message relevance, and social presence. Mediation analyses will use a multilevel structural equation model, accounting for missing data with full information maximum likelihood.

We will use GPS-based social opportunity and social isolation scores, quantity, and emotional quality of social interactions to test the direct effects of specific messages. We will also examine, at the within-persons level, whether message relevance (assessed in Day Reports after forced message exposure) mediates participants' in-person social interactions in the ensuing 24 hours. The model will produce bootstrapped 95% confidence intervals with 1,000 repetitions. We will confirm that mediation has occurred if the 95% confidence does not include zero. Activity 2b is possible even if the RCT results in unexpected null findings; examining the existence and magnitude of indirect effects and processes is both appropriate and critical for theory building. These analyses will provide evidence for how specific health communication messages are received and predict social behavior to reduce social isolation and loneliness.

### ACTIVITY 2C: TEST THEORY-DRIVEN MEDIATORS AND ROBUSTNESS WHEN CONTROLLING FOR ALTERNATIVE MEDIATORS.

Positivity Resonance Theory pinpoints the hypothesized mediator of our experimental health communication to be the emotional quality of social interactions. To test this, we will examine whether any observed effects on social opportunity and isolation, loneliness, and other secondary outcomes can be explained by improvements in positivity resonance. The pattern of change (slope and intercept) in weekly positivity resonance will be evaluated using the same growth modeling strategy (i.e., unconditional latent growth curve model and/or multilevel model) used above. Time-variant predictor positivity resonance will be added as a potential mediator to explain the link between randomized condition and changes in the GPS-based indices of social opportunity and social isolation. The direct effects of condition on the slope and the intercept of positivity resonance as well as the indirect effects of condition on social opportunity and social isolation via changes in positivity resonance will be estimated using path analyses. In later sensitivity analyses, all models will control for overall daily positive emotions and quantity of social interaction. We will repeat these analyses for self-reported loneliness (assessed separately for the Day Reports and Biweekly reports) and the following secondary outcomes: anxiety, depression, stress, flourishing mental health, life satisfaction, and belongingness. We will also test the following as mediators in place of positivity resonance (also controlling for overall daily positive emotions and quantity of social interaction in later sensitivity analyses):

Openness to social interactions

Initiation of social interactions

Safety/trust (Day Reports)

Additionally, we will test potential mediators for any indirect effects of condition on positivity resonance (with close ties, weak ties, and strangers assessed separately) using a similar analytic strategy as described above. We plan to test the following as potential mediators in these models:

Openness to social interactions

Initiation of social interactions

Safety/trust (Day Reports)

## AIM 3: BUILD FRAMEWORK

Extend analyses of the Keep Social RCT to identify context-specific and person-level moderators of reduced isolation and loneliness to identify where and for whom effects are largest.

### ACTIVITY 3A: COMPILE MACRO DATA ON SOCIAL STRUCTURES TO IDENTIFY STRUCTURAL BARRIERS AND ACCELERANTS.

Guided by current and emerging evidence on context-specific factors that influence health and social behavior (e.g., population density, walkability, crime), we will compile place-based factors by participants' county and/or zip code. Using the analytic model described above, context-specific moderators will be added one at a time to test whether these factors alter the degree to which our experimental health communication raises positivity resonance and/or reduces social isolation and loneliness.

### **ACTIVITY 3B: TEST MODERATION BY PERSON-LEVEL VARIABLES OR BY TIME-VARYING INDICES**.

Patterning Activity 3a, we will test person-level moderators (e.g., race, Latino/Hispanic ethnicity, subjective social status, gender identity) on the impact of our experimental health communication. We will also test time-varying moderators (e.g., behavioral adherence, experiences of incivility). Potential exploratory moderators include:

Race

Latino/Hispanic ethnicity

Subjective social status

Gender

Anticipated Discrimination

Bicultural Identity Integration

Food Insecurity

Identity Vitality-Pathology Scale (short)

Interaction Anxiousness

Neighborhood Disorder

Neighborhood Walking Environment

Perceived Economic Inequality

Community Financial Support

Race Salience

Race Salience Distress

Relational Mobility

Simpatía

Neighborhood Trust

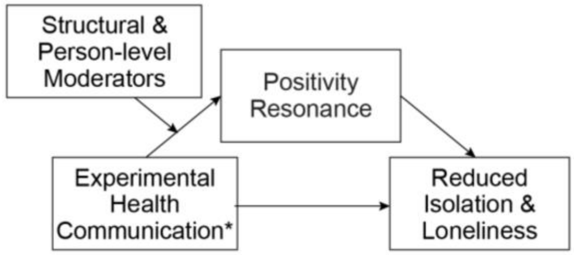
Geospatial variables measured at the levels of zip code, state, and/or county (e.g., Gini coefficient)

Passive Invibe feed background captures (e.g., number of posts seen, sum of all post likes, total time on posts in milliseconds, and sum of all post bookmarks)

### **ACTIVITY 3C: EXPLORE MEDIATOR(S) AND MODERATOR(S), SINGLY AND IN COMBINATION, IN THE KEEP SOCIAL RCT**.

Guided by the moderated mediation model in Figure 1, we will integrate insights from Activities 3a and 3b into a final model to create an evidence-based framework of key mechanism(s) and moderator(s) of social behavior change that is attuned to young adults who face higher disease burden. Building on the mediation model from Activity 2c, plausible moderators will be added to explore whether any demographic or psychological factors alter the effectiveness of our intervention for increasing positivity resonance. The final product of Activities 2a-3c will encapsulate generalizable knowledge about how, where, and for whom our experimental health communication reduces the risk factors of social isolation and loneliness that can guide efforts to further tailor and optimize these health messages for subsequent translational work to develop tailored interventions to promote health.

**Figure 1**. Guiding Conceptual Model: Moderated Mediation



*Randomization:* Experimental Social Connectedness Health Communication vs. Active Placebo Control

**Exploratory Analyses:**

What about the strength of social ties? Some participants may increase their in-person interactions with mostly strong social ties (e.g., close friends), whereas others may focus on weak social ties (e.g., community members) or strangers. We will explore whether between-participant variability in tie strength moderates the experimental effect by evaluating whether the proportion of weak social ties and the proportion of strangers alter the strength of the association between positivity resonance and our primary outcomes. We will operationalize the proportions for strangers as the average number of social interactions with the relevant social tie type (i.e., strangers or less familiar others), divided by the average number of total interactions across close other, less familiar others, and strangers.

To what extent does motivation for the recommended health behavior (Person-Activity Fit Scale) predict individuals' outcomes in the experimental group? We will test whether motivation for the recommended health behavior predicts all primary and secondary outcomes among those randomly assigned to the experimental group. (Note: this measure was not assessed in the control group, which is why we limit our analyses to only one condition.)

Our surveys also include a number of other scales that we may test as outcome measures, mediators, or moderators.

**Outliers and Data Exclusions:**

Assuming sufficient power, we intend to conduct tests of intervention efficacy by testing hypotheses with two samples: (a) an Intent-to-Treat sample, and b) a Per-Protocol sample.

- Our Intent-to-Treat sample includes all participants who remained enrolled at the stage of participant allocation to randomized conditions (Treatment or Control), i.e., the T2 Biweekly Assessment.

- Our Per-Protocol sample will include those who:
  - Were randomized to a condition at the T2 Biweekly Assessment (Treatment and Control groups)
  - Show an indication that the intervention video played in full (Treatment group only)
  - Provided sensical responses to the open-text requests for an if-then plan (Treatment group only)
  - Were exposed to at least 3 of the 12 reinforcing social media messages (Treatment and Control groups)

For the behavioral motivational value measure, the data from participants who miss more than 30 choices in the reinforcement learning task, who only click one side of the screen throughout the task, and/or who only choose one fractal throughout the task will be excluded from the analysis.

Otherwise, we do not intend to exclude observations. All exclusions will be reported clearly in published work.

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