Developing mHealth Interventions to Improve Mood, Activity, and Sleep for Medical Interns

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In collaboration with….

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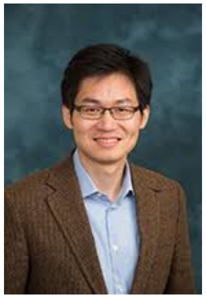
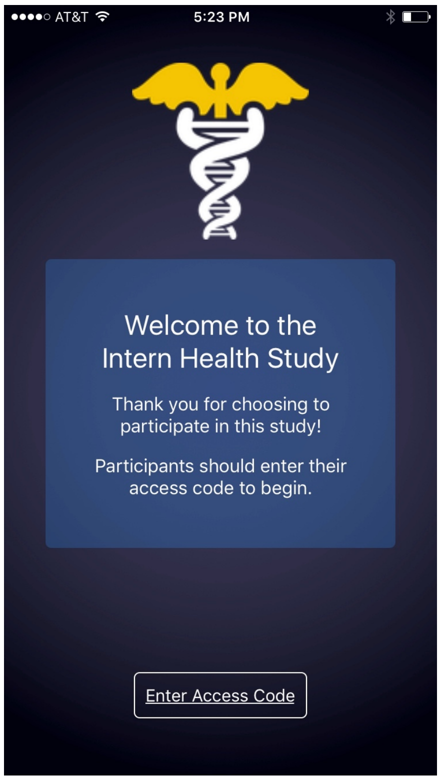


Overview

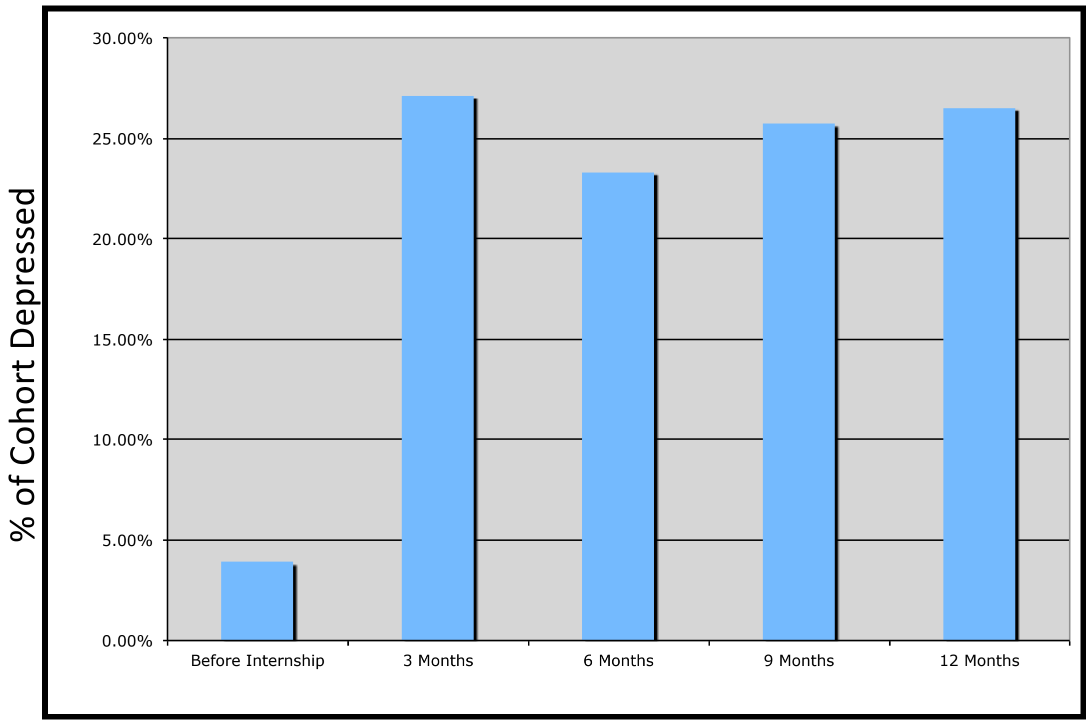
- Background
- Trial Design
- Missing data issues
- Results
- Conclusions and Future Work

Background- Intern Health Study



Intern Health Study-population

- A year long study on medical interns – medical doctors in their first year of residency



Sen, Srijan et al. "A prospective cohort study investigating factors associated with depression during medical internship" *Archives of general psychiatry* (2010)

Intern Health Study-data collection

- In 2018, for 2,111 medical interns we collect data using:
  - Fitbit
  - Phone - Self-reported mood
  - Survey (baseline + every 3 months) – PHQ 9 + more

In 2018, we also wanted to intervene

- Can we inspire positive behavior change in interns to help them during their internship year?
  - Maintain a positive mood
  - Have healthy sleep habits
  - Stay physically active

Intervention component: Data dashboard

- All interns have access to an application developed by Arbormoon

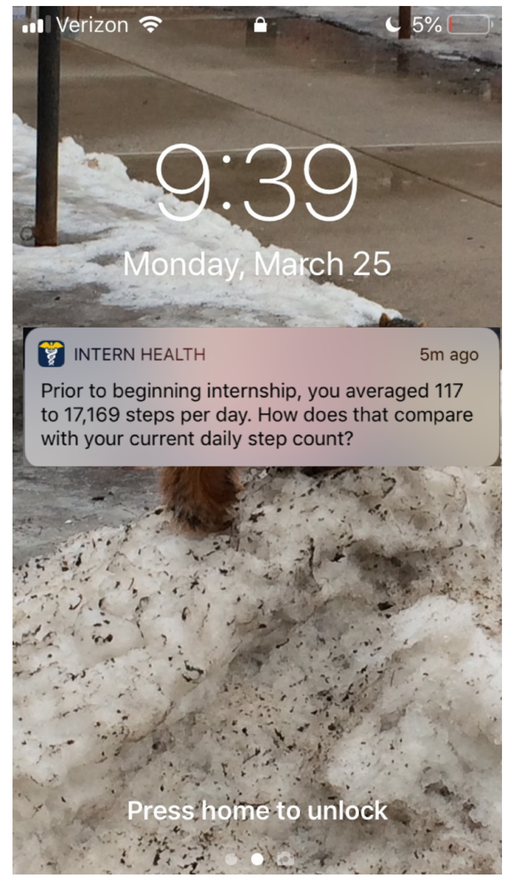
- The app gives data summaries

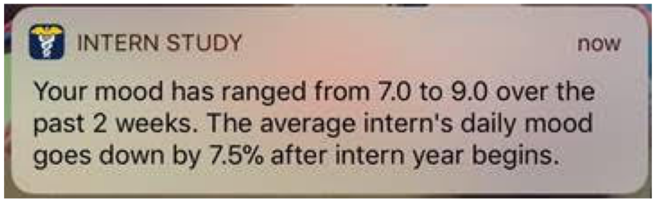
Intervention component: Push Notifications

(2 x 3 = 6 kinds of messages):

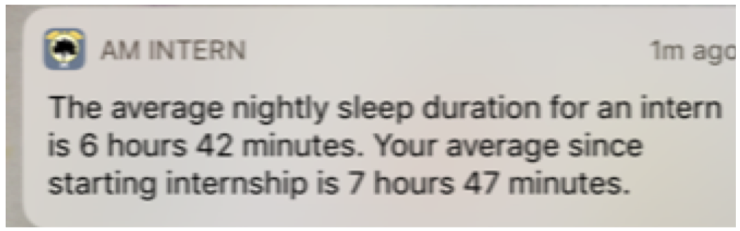
- Category:
  - Mood
  - Activity
  - Sleep

- Type:
  - Life insight – Data-driven message
  - Tip – General Advice, non data driven





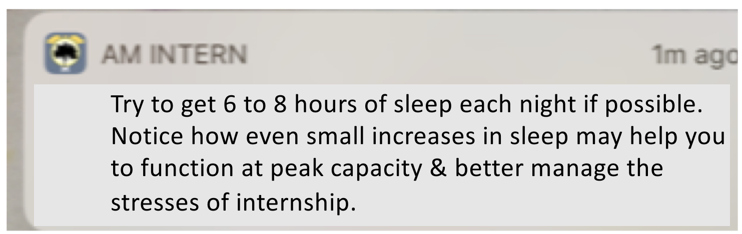
Mood life insight



Sleep life insight

Activity life insight

Mood life tip



Sleep tip

Activity tip

Research questions about these messages:

- How do different categories of messages affect mood, activity, and sleep?
- How do the effects of messages change based on previous mood, activity, and sleep?
- Do life insights affect interns differently than tips?
- How do messages affect long-term mental health of interns?

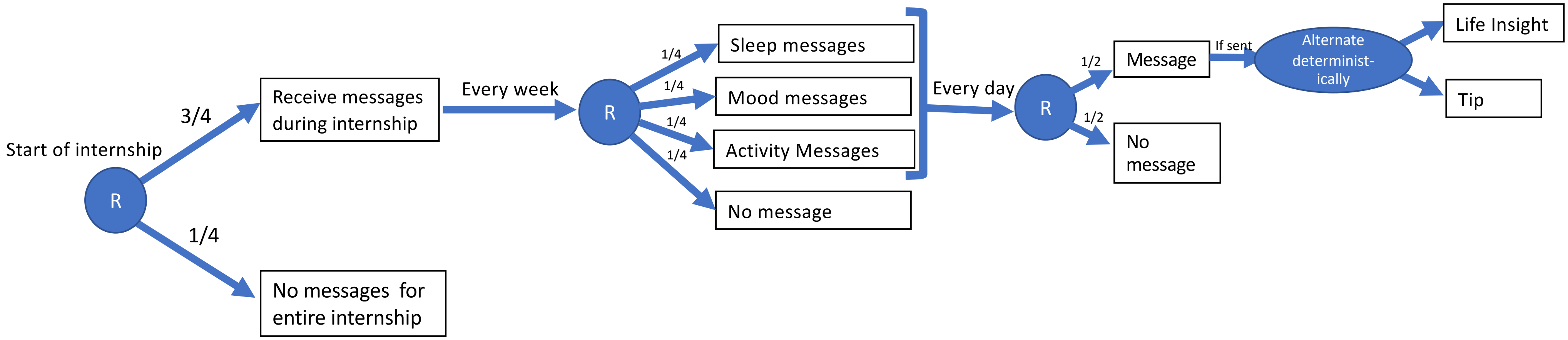
To answer these questions, we designed a micro-randomized trial

- Micro-randomized trials vs randomized control trial
  - Randomize each person many times throughout the trial

- Advantages of micro-randomized trial
  - Estimate short-term effects
  - Discover real-time moderators

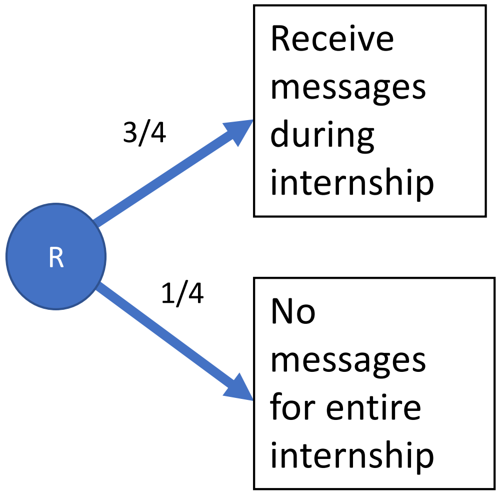
Klasnja, P. et al. “Microrandomized trials: An experimental design for developing just-in-time adaptive interventions” *Health psychology* (2015)

Randomization scheme



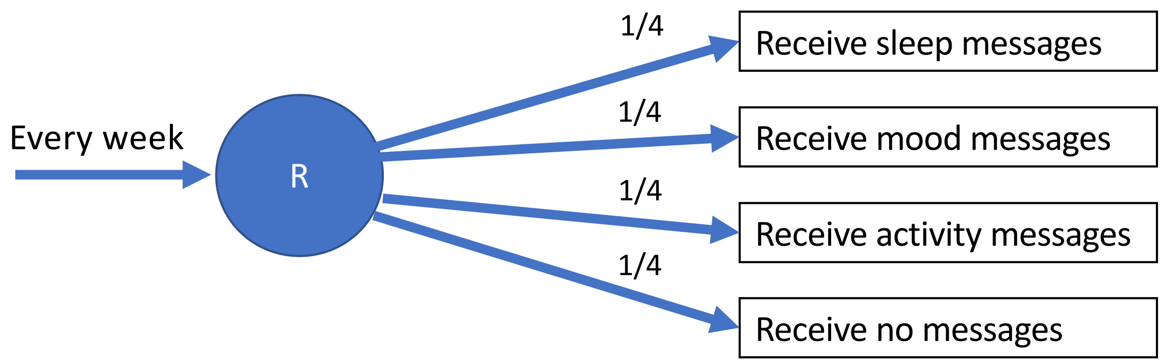
- Trial goes from June 30, 2018 - Dec 31, 2018 (6 months).
- Messages sent at 3 pm every day, mood scores typically entered around 8pm

Randomization 1: Pre-internship



- How do messages affect long-term mental health of interns (as measured by quarterly PHQ-9)?

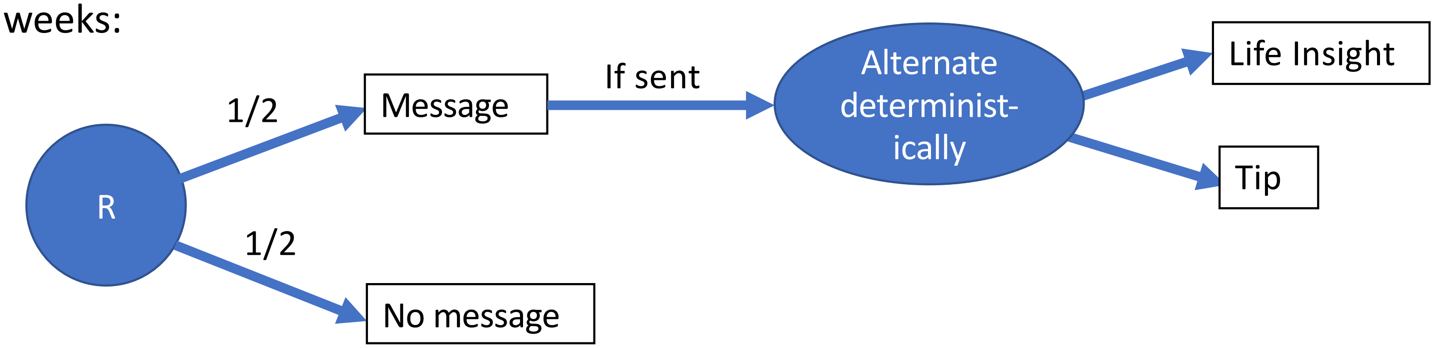
Randomization 2: Weekly message category



- How do different categories of messages affect mood, activity, and sleep?
- How do the effects of different categories change based on previous mood, activity, and sleep?

Randomization 3:
Daily randomization

For message weeks:



- Prevents burden and loss of engagement
- We can answer: How do life insights or tips compare to no message?

Sample size and trial data

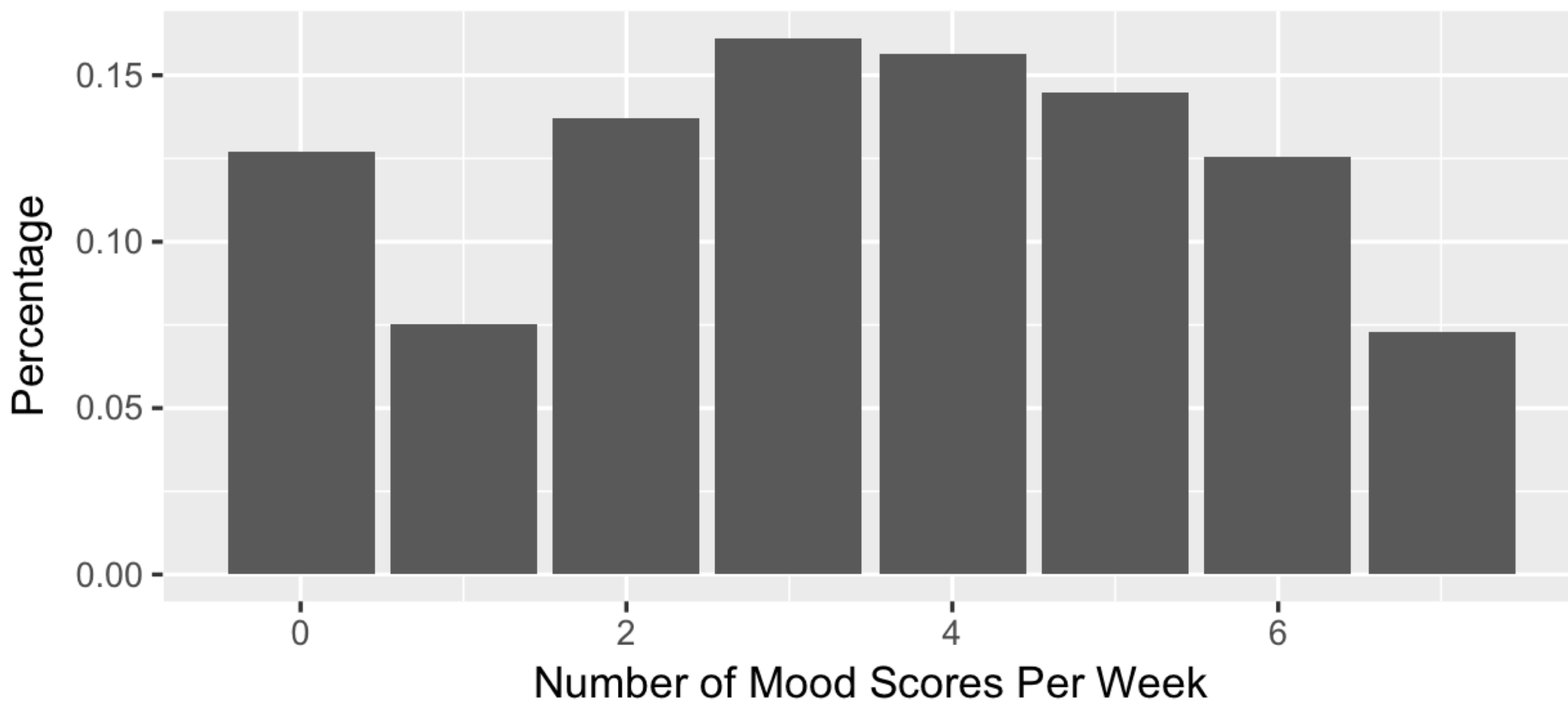
- Data collection started in April
  - Interventions were sent on June 30-Dec 31, 2018 (6 months or 26 weeks)
- 2111 interns in trial, 1565 are sent messages

Missing Data Issues

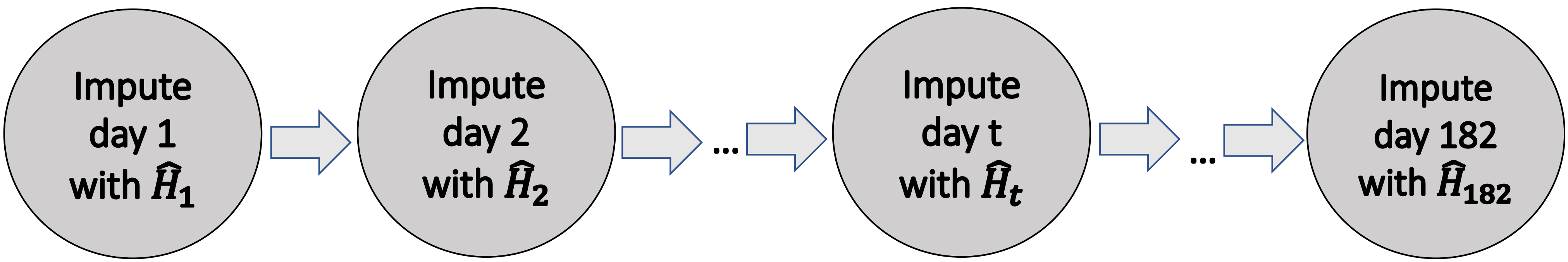
- Missing data is an issue with self-reported outcome
- Missing data is a problem in large mobile health studies
- I will give an overview of our missingness and proposed solution

Missingness over time

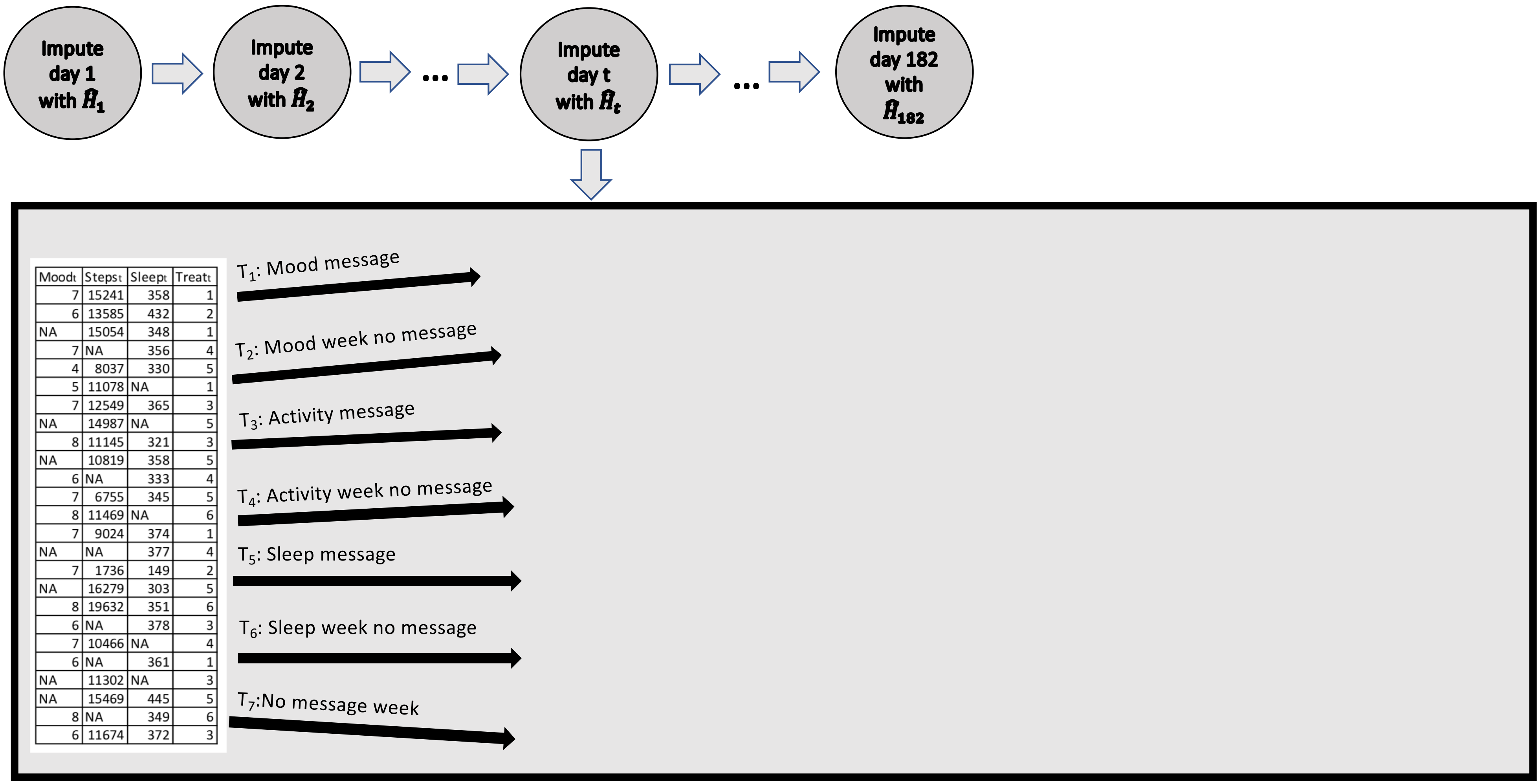
Number of mood scores for per week



Imputation algorithm-Sequential Imputation

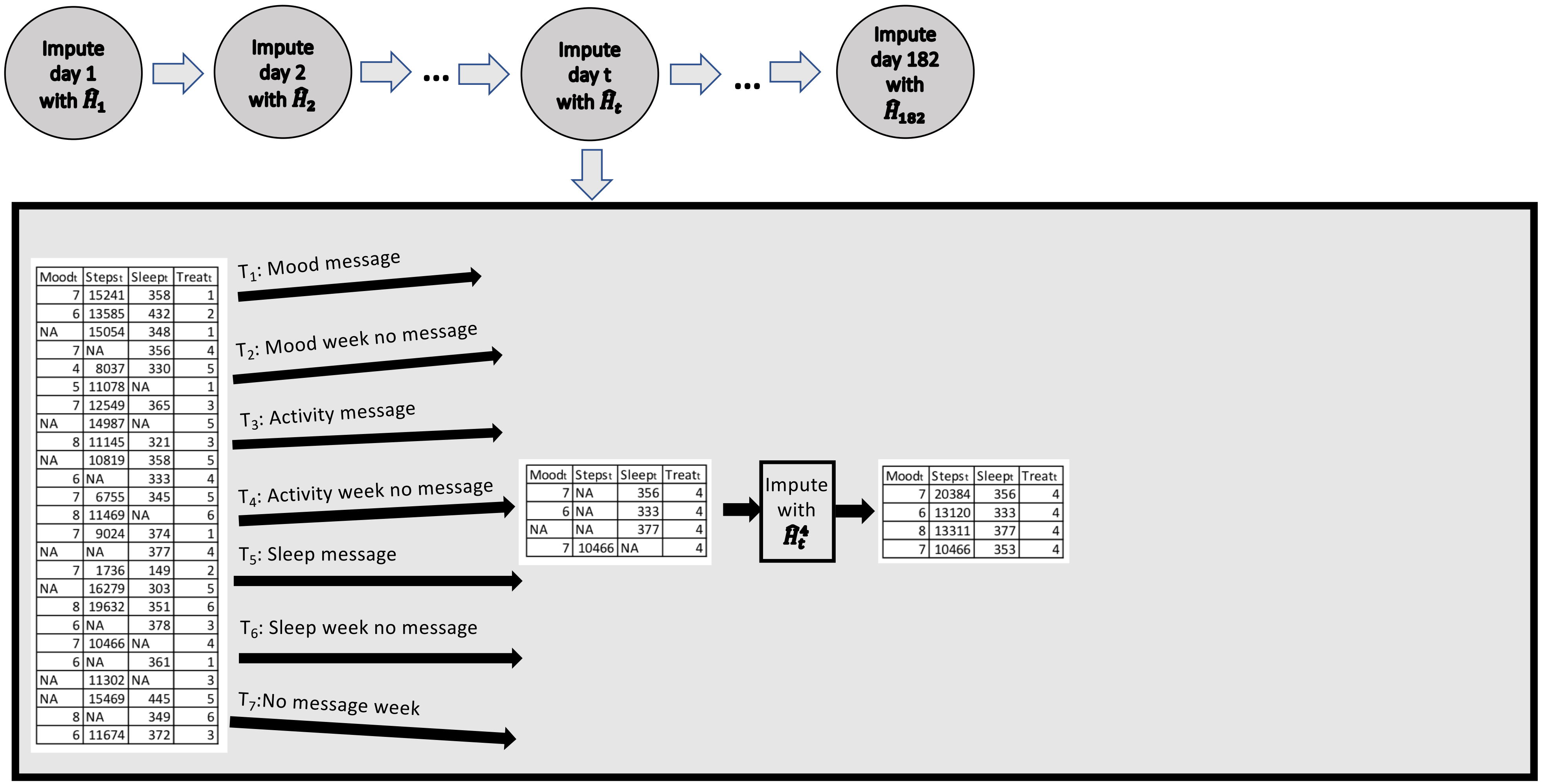


Imputation algorithm-Treatment group separation



$Mood_t$	$Steps_t$	$Sleep_t$	$Treat_t$
7	15241	358	1
6	13585	432	2
NA	15054	348	1
7	NA	356	4
4	8037	330	5
5	11078	NA	1
7	12549	365	3
NA	14987	NA	5
8	11145	321	3
NA	10819	358	5
6	NA	333	4
7	6755	345	5
8	11469	NA	6
7	9024	374	1
NA	NA	377	4
7	1736	149	2
NA	16279	303	5
8	19632	351	6
6	NA	378	3
7	10466	NA	4
6	NA	361	1
NA	11302	NA	3
NA	15469	445	5
8	NA	349	6
6	11674	372	3

Imputation algorithm-Treatment group separation



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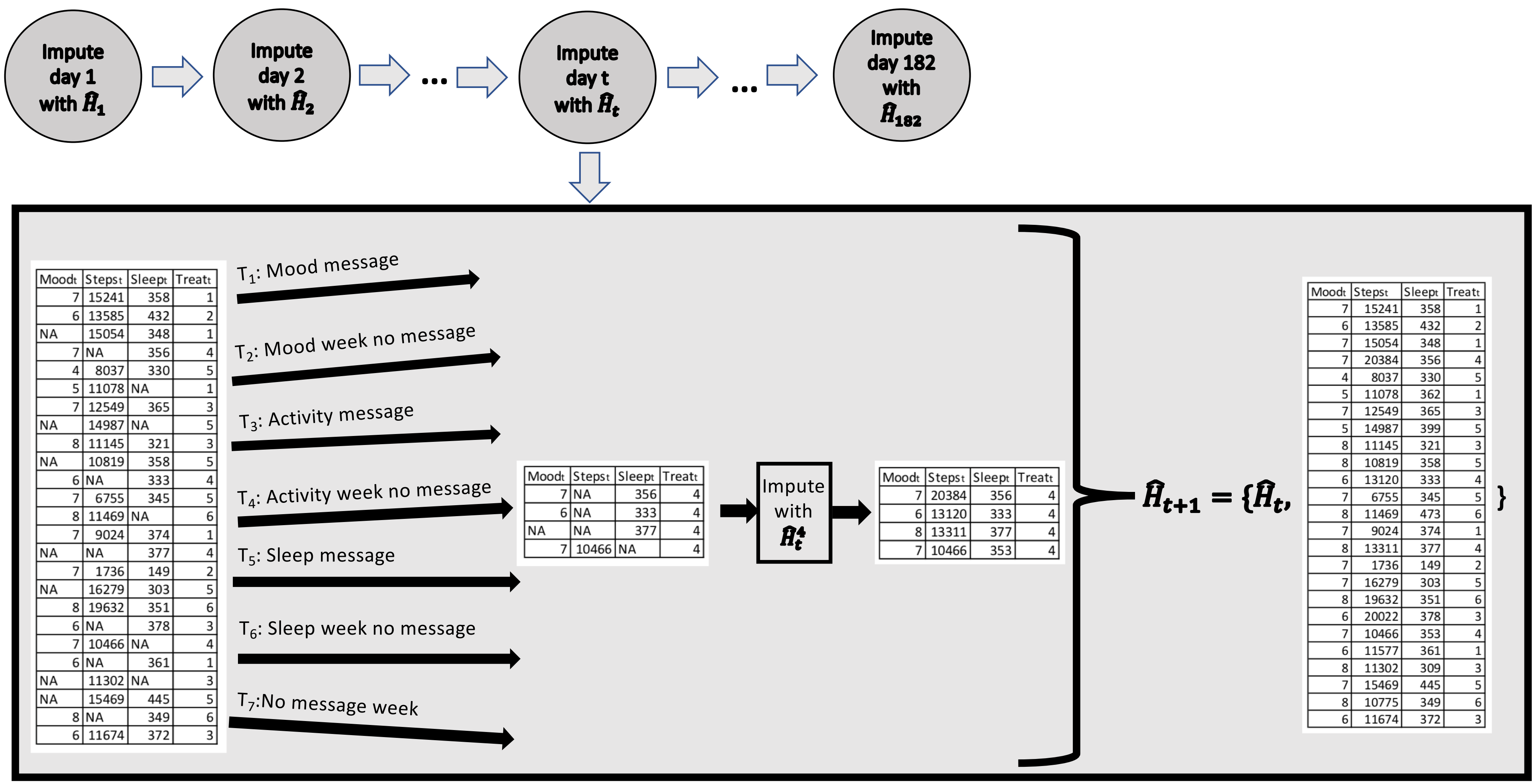
$Mood_t$	$Steps_t$	$Sleep_t$	$Treat_t$
7	20384	356	4
6	13120	333	4
8	13311	377	4
7	10466	353	4

Imputation-Update History



$Mood_t$	$Steps_t$	$Sleep_t$	$Treat_t$
7	15241	358	1
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8	11145	321	3
NA	10819	358	5
6	NA	333	4
7	6755	345	5
8	11469	NA	6
7	9024	374	1
NA	NA	377	4
7	1736	149	2
NA	16279	303	5
8	19632	351	6
6	NA	378	3
7	10466	NA	4
6	NA	361	1
NA	11302	NA	3
NA	15469	445	5
8	NA	349	6
6	11674	372	3

$Mood_t$	$Steps_t$	$Sleep_t$	$Treat_t$
7	NA	356	4
6	NA	333	4
NA	NA	377	4
7	10466	NA	4

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8	11469	473	6
7	9024	374	1
8	13311	377	4
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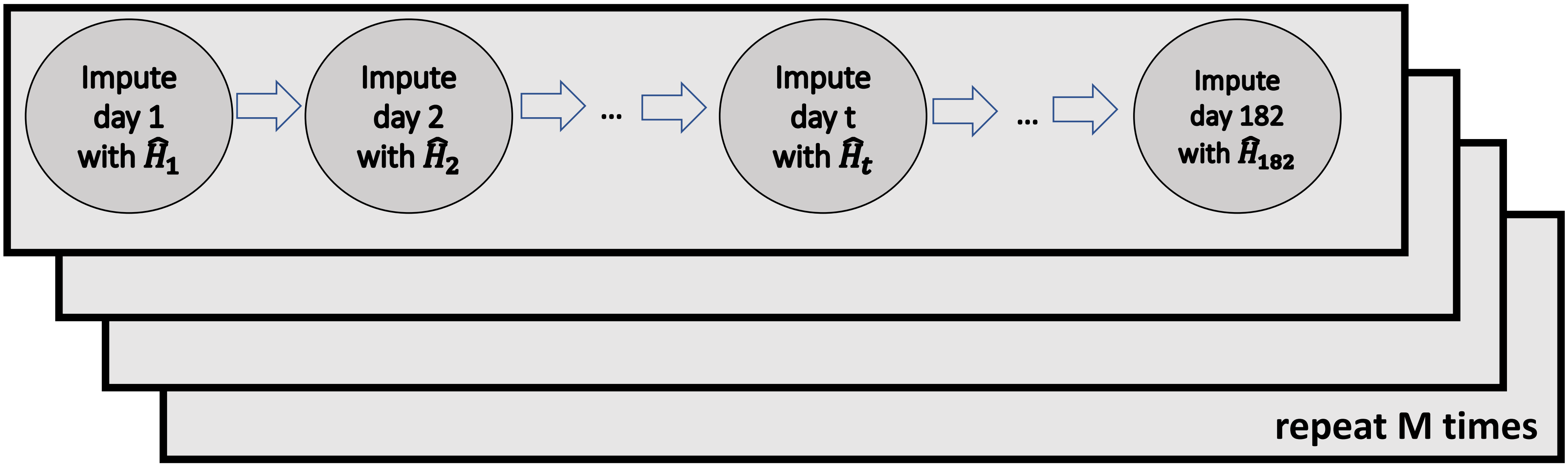
7	16279	303	5
8	19632	351	6
6	20022	378	3
7	10466	353	4
6	11577	361	1
8	11302	309	3
7	15469	445	5
8	10775	349	6
6	11674	372	3

Imputation algorithm-Multiple imputation



Concerns when imputing in micro-randomized trials

- Separating treatment groups vs sample size
- Sharing information over time
- Flexible imputation vs stable imputation
  - How to choose variables for imputation model

Analysis techniques for estimating proximal treatment effects

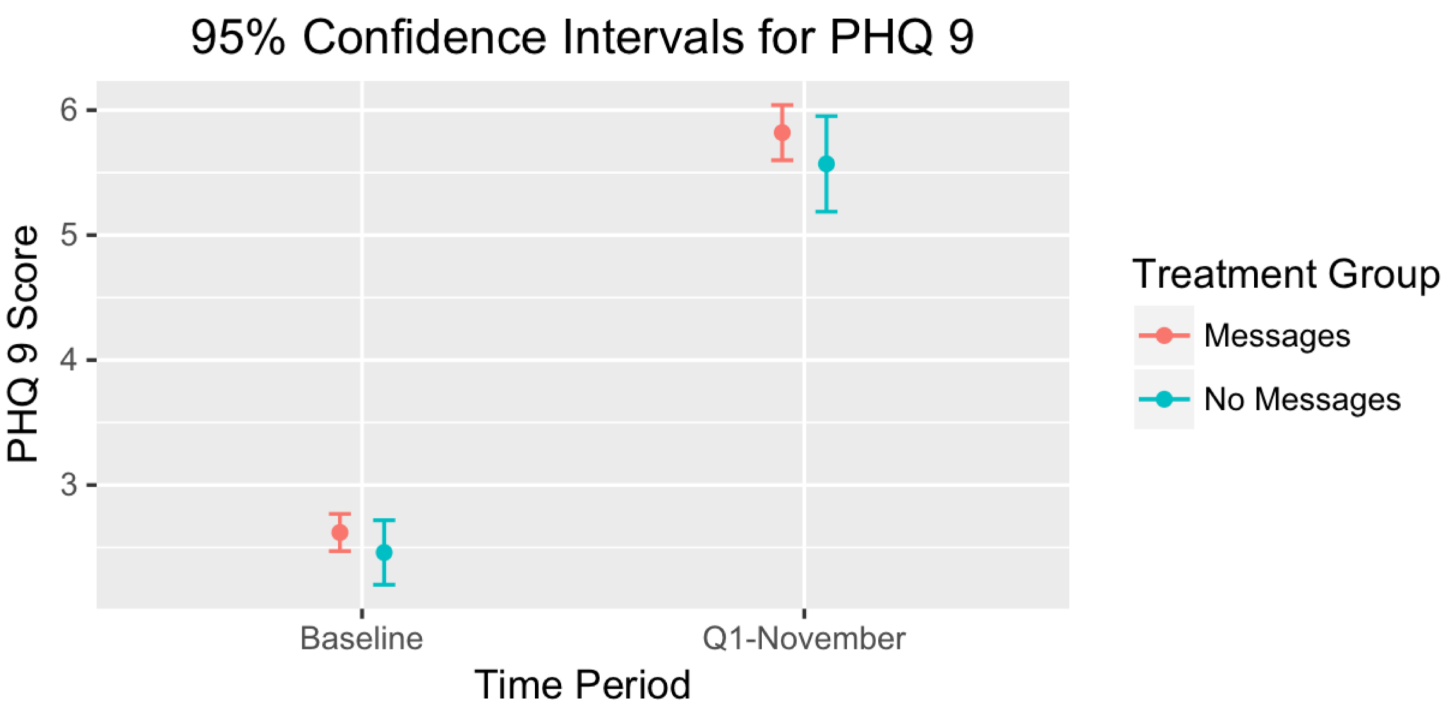
- Weighting and centering approach
- Estimating equation with robust standard errors
- Combine across imputation methods using Rubin’s rules

Boruvka, Almirall, Witkiewitz, and Murphy. *Assessing Time-varying Causal Effect Moderation in Mobile Health.* *JASA* (2018)

Main effects

- How do different messages perform overall on the category of interest?

How do messages affect long-term mental health of interns?



How do messages affect mood, activity, sleep?

Outcome

Message type

	Mood	Activity	Sleep
General	-.029 (p = .003)		
Mood			
Activity			
Sleep			

How do messages affect mood, activity, sleep?

Outcome

Message type

	Mood	Activity	Sleep
General	-.029 (p = .003)		
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Activity			
Sleep			

How do messages affect mood, activity, sleep?

Outcome

Message type

	Mood	Activity	Sleep
General	-.029 (p = .003)		
Mood	-.023 (p = .153)		
Activity		.088 (p = .075)	
Sleep			

123 steps increase in average daily activity per week

How do messages affect mood, activity, sleep?

		Outcome	
Message type	Mood	Activity	Sleep
General	-.029 (p = .003)		
Mood	-.023 (p = .153)		
Activity		.088 (p = .075)	
Sleep			.051 (p = .073)

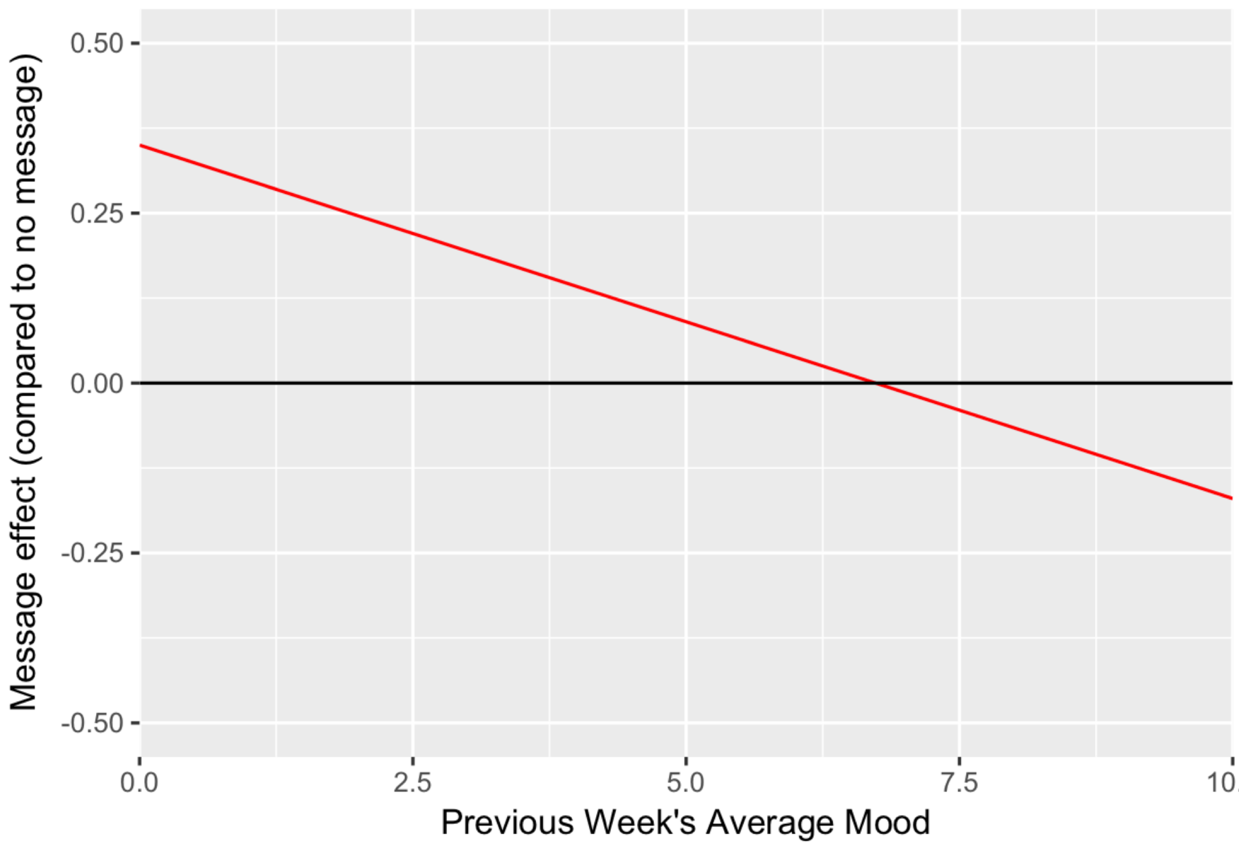
2 minutes of sleep in average daily sleep per week

Moderators analysis

- Moderator - a variable collected prior to intervention delivery that ‘moderates’ (or changes) the efficacy of an intervention

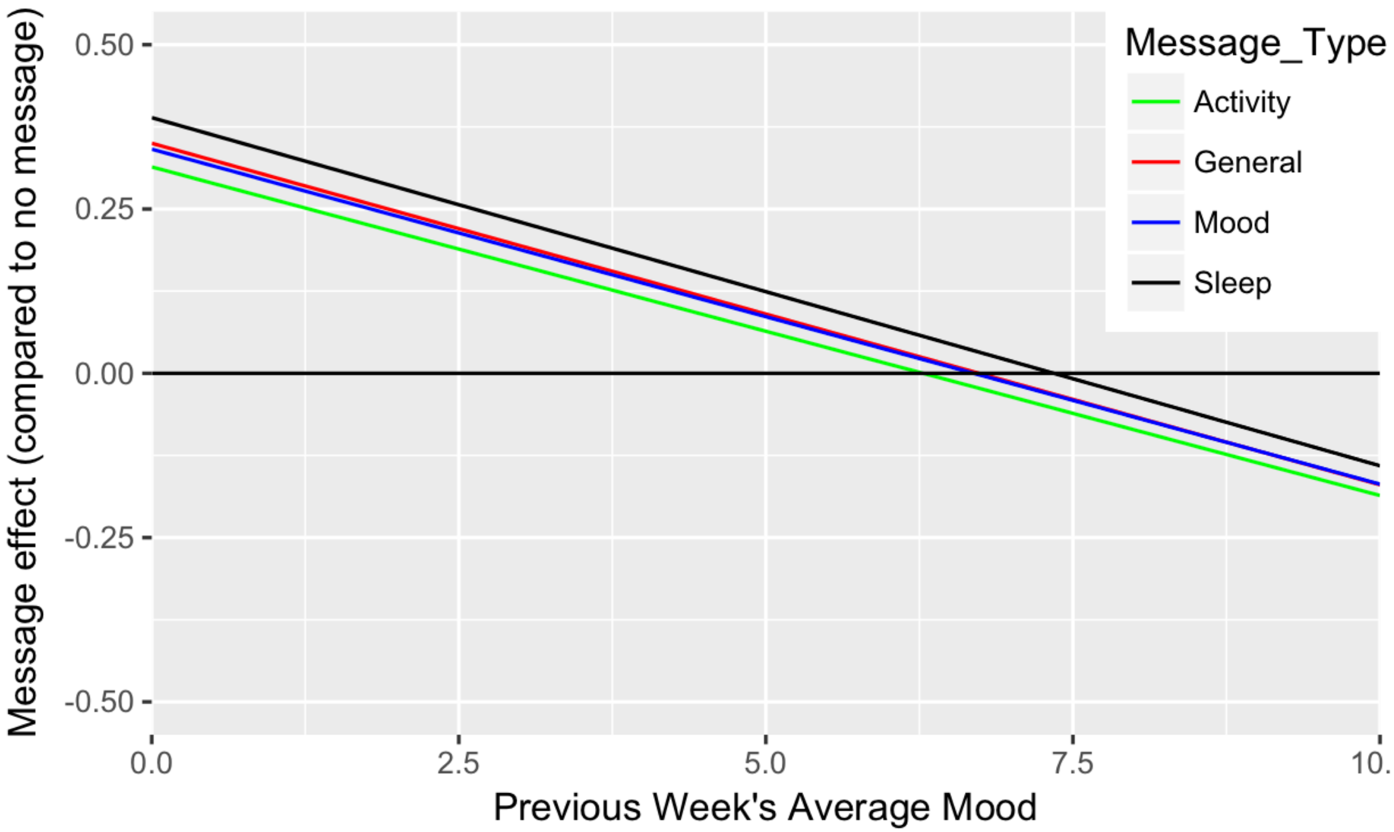
- How do these effects differ based on previously collected data?

Are the effects of messages (in general) on mood moderated by previous week's mood?



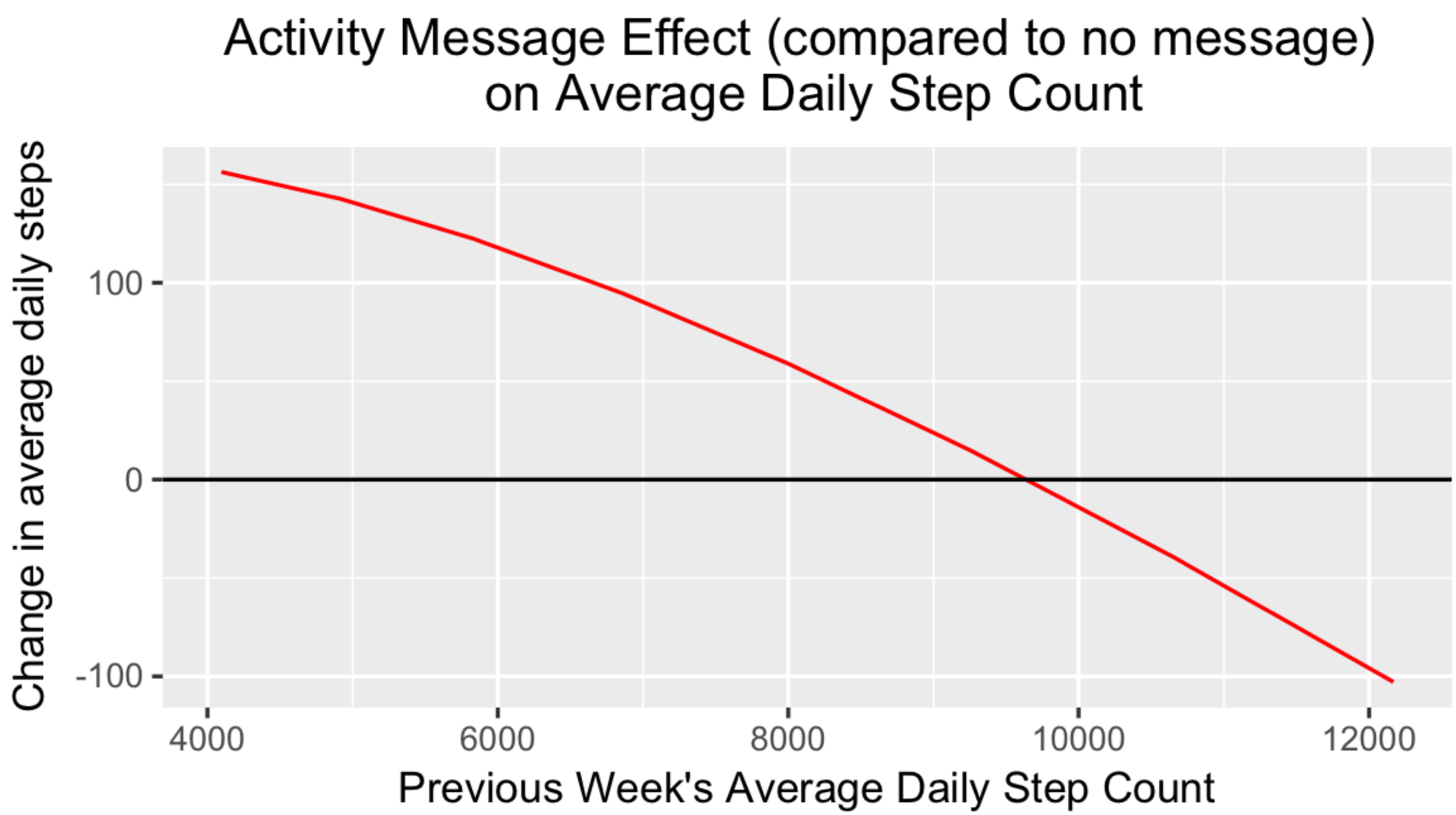
slope = -.052, p-value = .001

The negative moderation is true across all message categories



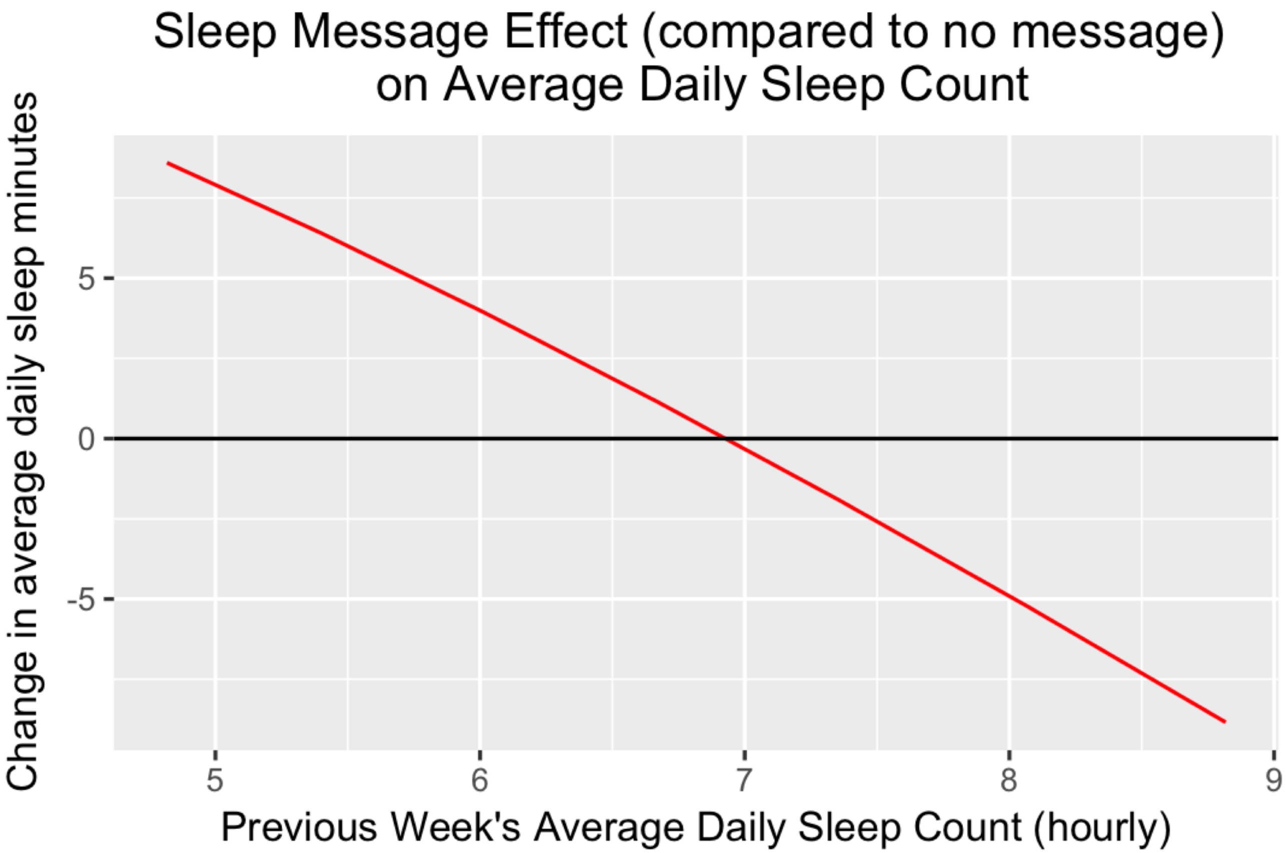
Mood
slope = -.051, p-value = .004
Activity
slope = -.050, p-value = .006
Sleep
slope = -.053, p-value = .001

Are the effects of activity messages on activity moderated by previous week’s activity?



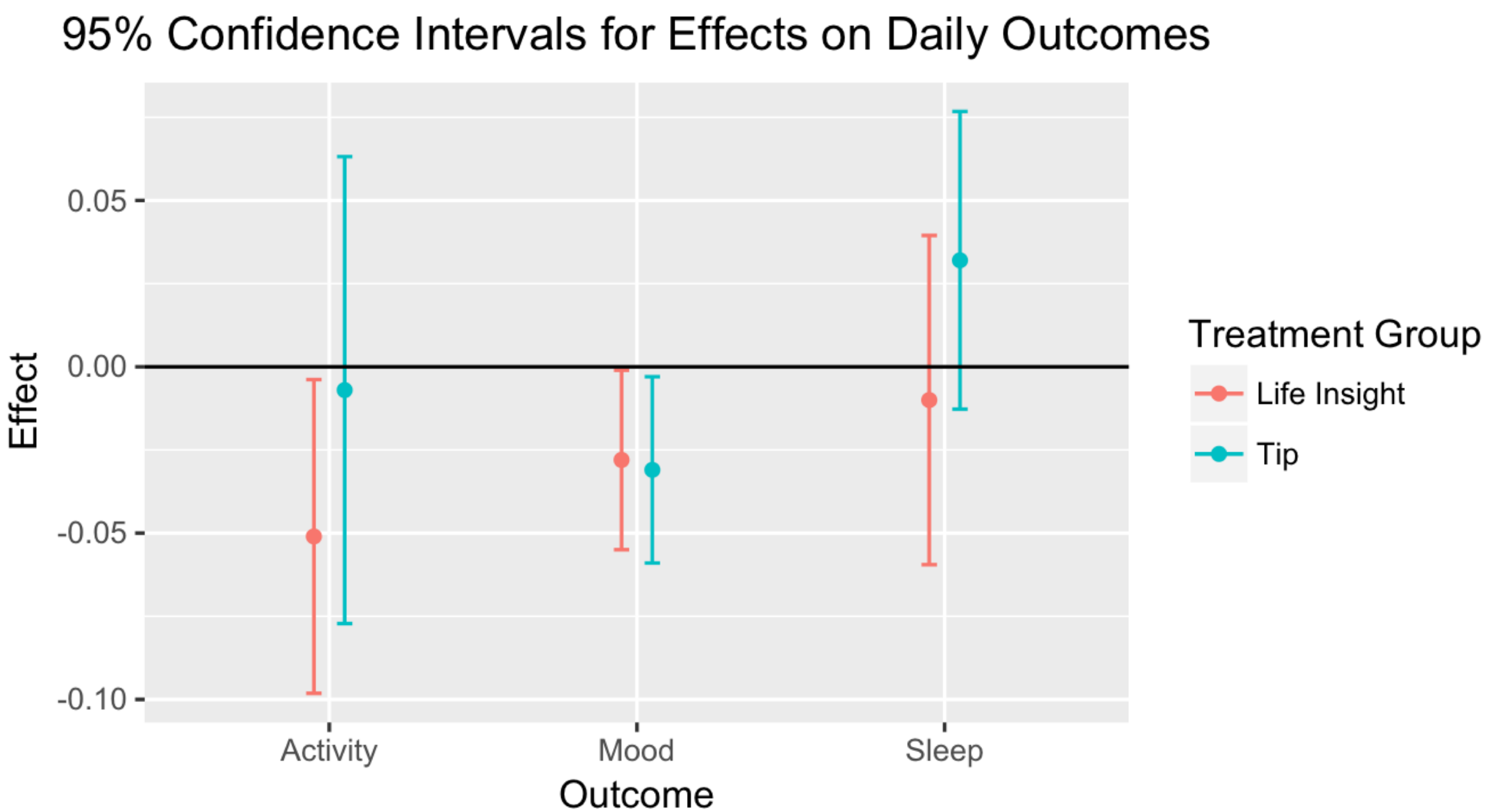
Slope = -.038
(on cube root scale),
p-value = .033

Are the effects of sleep messages on sleep moderated by previous week's sleep?



slope = -.074
(on square root scale)
p-value = .007

How do life insights compare to tips?



Conclusions

- Main effects are there, but effect sizes are small
- Moderator effects indicate that messages should be tailored
- No big difference between life insights and tips
- No big change on long-term mental health

Informing the 2019 Trial Design

- Changes for 2019:
  - Including a new (sub)category: Circadian
  - Message tailoring
  - Eliminating weekly level randomization
  - Obtain work schedule data

Future work

- Causally valid + practical + low variance imputation scheme
- Extend methods to ordinal data
- Share information over several cohorts

Thanks!

References

- Boruvka, Almirall, Witkiewitz, and Murphy. *Assessing Time-varying Causal Effect Moderation in Mobile Health. JASA* (2018)
- Klasnja, P. et al. "Microrandomized trials: An experimental design for developing just-in-time adaptive interventions" *Health psychology* (2015)
- Sen, Srijan et al. "A prospective cohort study investigating factors associated with depression during medical internship" *Archives of general psychiatry* (2010)

Extra slides

Imputation algorithm-

For t in 1:183:

Create groups for each daily treatment group:

G_1 = {individuals s.t. get mood message on day t}
G_2 = {individuals s.t. in mood week, but get no message day t}
G_3 = {individuals s.t. get activity message on day t}
G_4 = {individuals s.t. in activity week, but get no message day t}
G_5 = {individuals s.t. get sleep message on day t}
G_6 = {individuals s.t. in sleep week, but get no message day t}
G_7 = {individuals s.t. in no message week}

Impute groups separately

For k in 1:7:

For all i in G_k, impute $Mood_{it}^{0}, Activity_{it}^{0}, Sleep_{it}^{0}$ using {H_{jt}, $Mood_{jt}^{1}, Activity_{jt}^{1}, Sleep_{jt}^{1}$ for j in G_k and H_{it}},

H_{jt} is complete, imputed historical data
$Mood_{jt}^{1}$ is non-missing mood values
$Mood_{jt}^{0}$ are missing mood values