Mobile Health

Lecture 12
Mobile Devices and Behaviour Interventions

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Mobile Devices and Passive Sensing

- We have seen how various sensors on devices are able to sense our behaviour and this can be indicative of disease.

- In this lecture we will talk about the use of this sensing and the possible interventions which can be guided by this data.

What is a "digital intervention"?

- Make sense of the passive data collected to inform what to tell the user (i.e. how to solicit a positive behaviour in the user)

  - Avoid the person to smoke while on a smoke cessation program
  - Remind people to take their medications
  - Solicit the person to do breathing exercises to reduce stress
  - Remind them to walk more…
  - Support someone in their diet

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Pull Interventions

- Interventions where it is the user who requests them

- Example: someone checking how many steps they have done in a day

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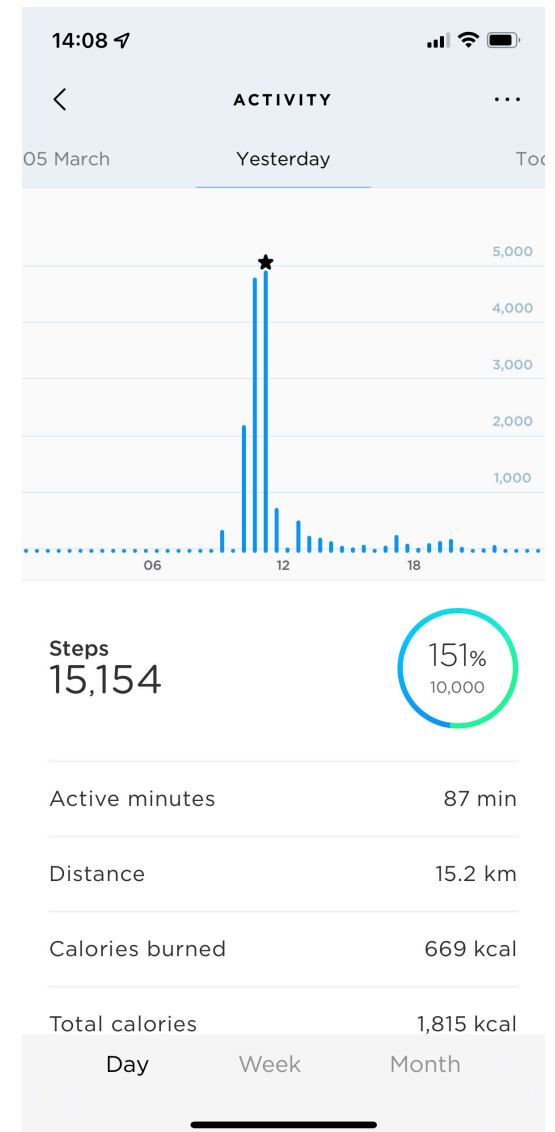
Push Intervention

- A device prompting a user with a message

Smoking Cessation Behaviour Intervention
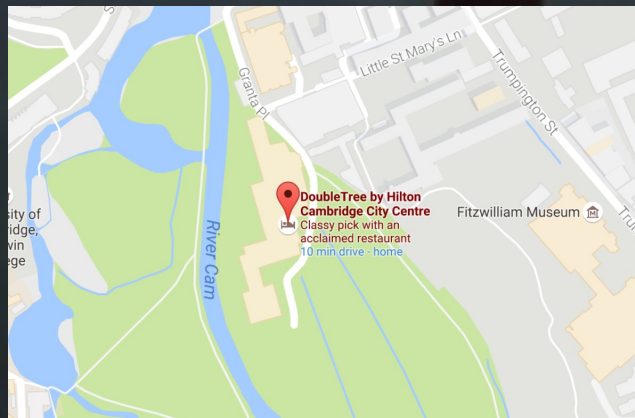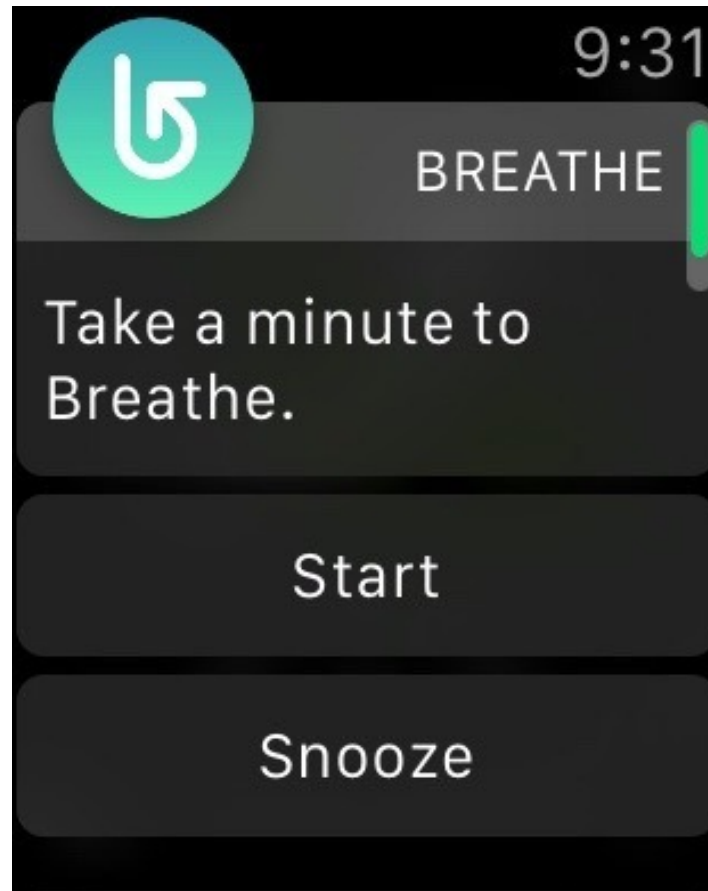
What form does a digital intervention take?

Challenges

- What message to send (to this user)

- When to send it (avoid bad times, find best times) avoid times where you are doing other things when interventions are useless

- How do we know it worked! Randomization…

What message

- Some messages might involve more user attention
- Some messages might be better than others depending on
  - User (what message does this user answer most often to?)
  - Context (in some time of day some intervention is better than another)
- Psychology (we won't discuss)

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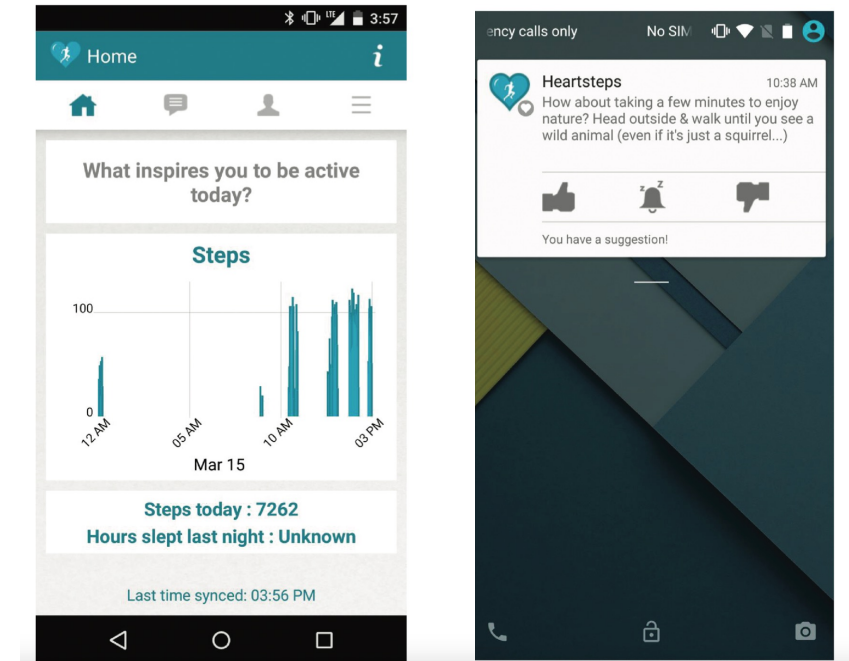
HeartSteps Messages and Context

Suggestion	Type	Time of day	Day of the week	Weather	Location
Is there anything better than weekend afternoons? You could enjoy the fresh air by taking a walk around your neighborhood!	Walking	Midafternoon	Weekend	Suitable for walking outside	Home
While eating at your desk can be tempting, lunch is your time for a much-needed mental break. Can you take a few minutes to stand & stretch?	Antisedentary	Lunch	Weekdays	Any	Work
This evening would be a good time for a challenge: a walk in bad weather. Bundle up & enjoy the outdoors!	Walking	Postdinner	Weekdays Weekends	Snow	Home
Have a long conference call today? Walking in place or pacing while you talk can keep you engaged and increase your step count!	Walking	Morning Midafternoon	Weekdays	Not suitable for walking outside	Work
When's the last time you dusted? If you have 5 minutes, you could grab a feather duster & take a crack at those end tables!	Antisedentary	Morning Lunch Midafternoon Late afternoon	Weekdays Weekend	Any	Home
Have you been sitting at your desk all morning? Why not stand up & do some light stretches for 2–3 minutes? It will energize you for the rest of the day!	Antisedentary	Lunch	Weekdays	Any	Work

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QuitSense messages

tip_id	tip_index	time_of_day	stressed_rating	depressed_rating	craving_rating	current_situation	other_smokers	fence_event	header	message	BC
GF00041	41	["early_am","daytime","late_pm"]	["Somewhat","Very","Extremely"]		["Strong","Very Strong","Extremely Strong"]	["Working"]	["Who are smoking"]	["Entry"]	Managing at work	Some people find that they can reduce stress at work by prioritising their work, breaking tasks into smaller steps, or talking through any problems. Deep breathing and having breaks can help too.	BS
GF00042	42	["early_am","daytime","late_pm"]	["Somewhat","Very","Extremely"]		["Slight","Moderate"]	["Working"]	["Who are smoking"]	["Entry"]	Managing at work	Some people find that they can reduce stress at work by prioritising their work, breaking tasks into smaller steps, or talking through any problems. Deep breathing and having breaks can help too.	
GF00043	43	["early_am","daytime","late_pm"]	["Somewhat","Very","Extremely"]		["Strong","Very Strong","Extremely Strong"]	["Working"]	["Who are not smoking","I am alone"]	["Entry"]	Managing at work	Some people find that they can reduce stress at work by prioritising their work, breaking tasks into smaller steps, or talking through any problems. Deep breathing and having breaks can help too.	
GF00044	44	["early_am","daytime","late_pm"]	["Somewhat","Very","Extremely"]		["Slight","Moderate"]	["Working"]	["Who are not smoking","I am alone"]	["Entry"]	Managing at work	Some people find that they can reduce stress at work by prioritising their work, breaking tasks into smaller steps, or talking through any problems. Deep breathing and having breaks can help too.	
GF00045	45	["early_am","daytime","late_pm"]	["Not at all","Slightly"]		["Strong","Very Strong","Extremely Strong"]	["Working"]	["Who are smoking"]	["Entry"]	Managing at work	Try to avoid taking breaks with people you used to smoke with. If this isn't possible, avoid seeing them smoking by taking a short walk instead.	
GF00046	46	["early_am","daytime","late_pm"]	["Not at all","Slightly"]		["Slight","Moderate"]	["Working"]	["Who are smoking"]	["Entry"]	Managing at work	Try to avoid taking breaks with people you used to smoke with. If this isn't possible, avoid seeing them smoking by taking a short walk instead.	
GF00047	47	["early_am","daytime","late_pm"]	["Not at all","Slightly"]		["Strong","Very Strong","Extremely Strong"]	["Working"]	["Who are not smoking","I am alone"]	["Entry"]	Managing at work	Having a brisk walk or taking slow deep breaths can help with urges. Also, keeping your mouth busy with gum or healthy snacks can help too.	
GF00048	48	["early_am","daytime","late_pm"]	["Not at all","Slightly"]		["Slight","Moderate"]	["Working"]	["Who are not smoking","I am alone"]	["Entry"]	Managing at work	Having a brisk walk or taking slow deep breaths can help with urges. Also, keeping your mouth busy with gum or healthy snacks can help too.	

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Naughton F, Brown C, High J, Notley C, Mascolo C, Coleman T, Barton G, Shepstone L, Sutton S, Prevost AT, Crane D, Greaves F, Hope A. Randomised controlled trial of a just-in-time adaptive intervention (JITAI) smoking cessation smartphone app: the Quit Sense feasibility trial protocol. BMJ Open. 2021 Apr 26;11(4).

When to send the message

- Depends on application and context.
- Context can be sensed
  - Location,
  - social through BLE,
  - time,
  - microphone for surrounding sounds and ambience,
  - activity through IMU
  - …

How do we know if an intervention works?

- We want to know what messages work when and for whom

- Factors which could be studied in parallel
  - Weather
  - Time of message
  - User characteristics/demographics

- Randomization allows to control for this variance in users and context
  - Why: because the messages will be sent at random times to random users so these conditions won't always be the same.

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Micro-randomization (HeartSteps)

- 5 times a day

- 30% chance message sent, 70% message not sent (per user)

- One evening message to plan for the day after (50% chance message)

- Messages: two types of suggestions (one more burdersome than another)

- Step count recorded in the 30 min following the randomization of suggestion delivery

Liao P, Greenewald K, Klasnja P, Murphy S. Personalized HeartSteps: A Reinforcement Learning Algorithm for Optimizing Physical Activity. Proc ACM Interact Mob Wearable Ubiquitous Technol. 2020 Mar;4(1):18. doi: 10.1145/3381007. PMID: 34527853; PMCID: PMC8439432.

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Sensing when not a good time to deliver a suggestion

- Users randomized only when available
- Availability
  - User based: I am in a meeting
  - Sensor based: User already doing an activity (eg already walking)

Results

- Providing a suggestion versus providing no suggestion initially increased the 30-min post-randomization step count by 66%, adding 167 steps to the 253-step average on the first day of the study.

- This effect diminished linearly over time at 2% per day and was no longer distinguishable from zero by the 28th day in the study. **People habituate!**

- Probabilities of delivery of intervention are static!

Reinforcement Learning (RL) and Personalization

- What if we adapt the probability of intervention to previous behaviour?

- HeartSteps V2 messages are delivered only when the participant has been sedentary during the past 40 minutes, with the randomization probability being adjusted on the fly to meet the average constraint on the number of anti-sedentary messages sent per day.

- Data from HeartSteps V1 used to inform the design of the RL algorithm for HeartSteps V2.

Liao P, Greenewald K, Klasnja P, Murphy S. Personalized HeartSteps: A Reinforcement Learning Algorithm for Optimizing Physical Activity. Proc ACM Interact Mob Wearable Ubiquitous Technol. 2020 Mar;4(1):18. doi: 10.1145/3381007. PMID: 34527853; PMCID: PMC8439432.

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RL Framework: Actions and Rewards

$\{S1, A1, R1, S2, A2, R2, \ldots, St, At, Rt, \cdots\}$

$At \in A$ (binary) action at time t (send or not send message)

Rt is the reward (is the user walking in the 30 mins following the action)

Note: Raw step counts can be highly noisy and positively skewed. The reward is the log-transformed step count where the log transformation is to make the reward distribution more symmetric and less heavy-tailed.

RL Framework: States

St = {It,Zt,Xt}

It: is the user available?

Zt: features
- current location,
- the prior 30-minute step count,
- yesterday's daily step count,
- the current temperature (weather),
- Measures how active participant has been around the current decision time over the last week.

- Xt: treatment burden: it's a discount if the user was sent lots of messages

Action Planning

$$r_t(s, 1) - r_t(s, 0) = f(s)^\top \beta$$

$$\Pr\left\{ f(s)^\top \beta > \eta_d(x); \ \beta \sim \mathcal{N}(\mu_d, \Sigma_d) \right\}$$

An action A is drawn from a Bernoulli distribution with probability derived from the above.

F(s) is the feature vector of the state (indicating location, app engagement, previous dosage and step variation)

Beta is Gaussian and depends on the posterior distribution derived on the previous day.
η proxies long term effects of delivering a given the dosage treatment burden Xd
[probability is also clipped]

Action Planning

feature vector

$$r_t(s, 1) - r_t(s, 0) = f(s)^\top \beta$$

→ *reward advantage*

$$\Pr\{f(s)^\top \beta > \eta_d(x); \beta \sim \mathcal{N}(\mu_d, \Sigma_d)\}$$ → *probabilities of switching*

An action A is drawn from a Bernoulli distribution with probability derived from the above.

F(s) is the feature vector of the state (indicating location, app engagement, previous dosage and step variation

**Beta** is Gaussian and depends on the posterior distribution derived on the previous day.
η proxies long term effects of delivering a given the dosage treatment burden Xd
[probability is also clipped]

Results

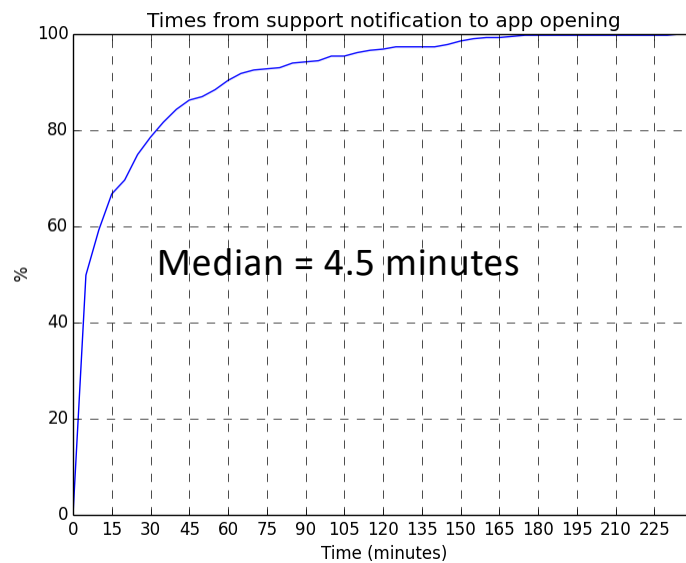| Participant ID	Days in the study	Average 30-minute steps in the first week	Average 30-minute steps after the first week	Difference
5	32	318.13	561.43	243.29
7	56	343.79	574.53	230.75
1	36	252.12	424.31	172.19
3	32	163.24	295.45	132.21
8	18	281.65	387.86	106.21
6	43	215.45	314.17	98.71
2	22	361.26	418.60	57.35
4	75	368.50	330.03	-38.47

Results
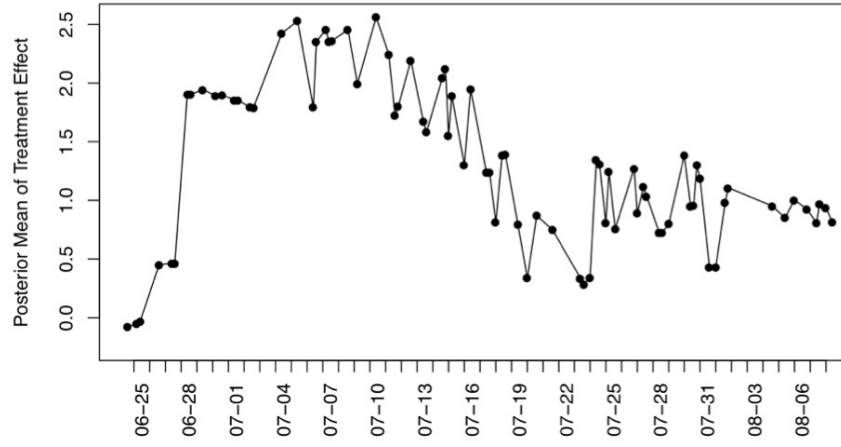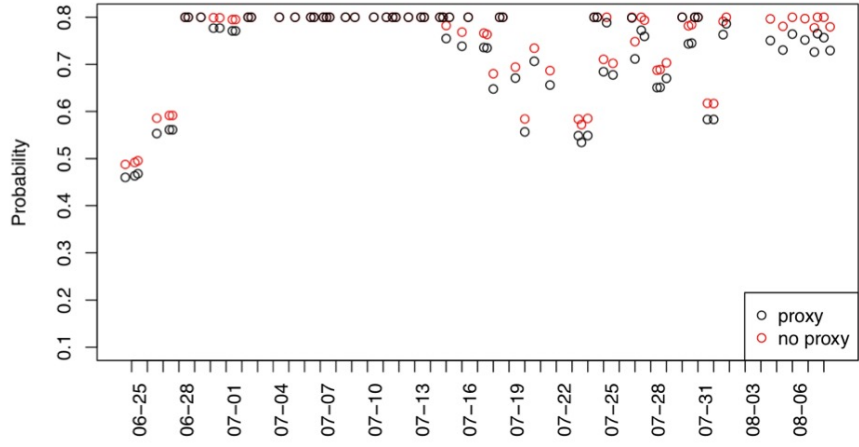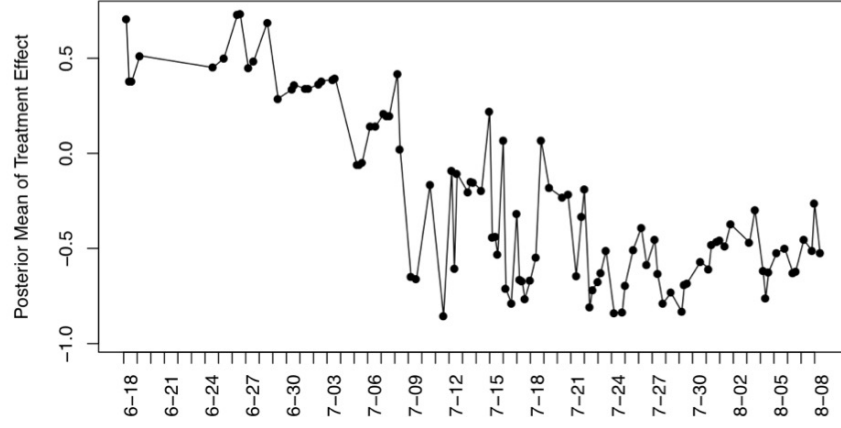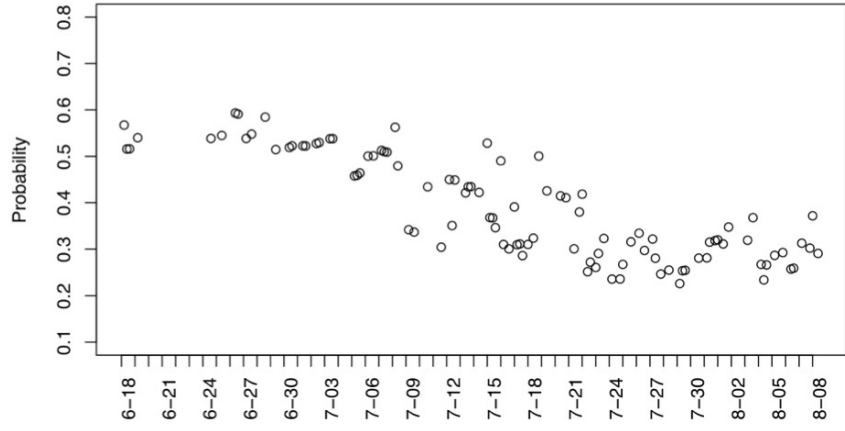
QuitSense: smoke cessation
(Speed of) Engagement

Median time to response after geofence message notification (n=15) = 4.5 mins

Geofence messages

Times from support notification to app opening

Median = 4.5 minutes

79% viewed within 30 minutes

Daily support messages

Times from countdown notification to app opening

Median = 24.2 minutes
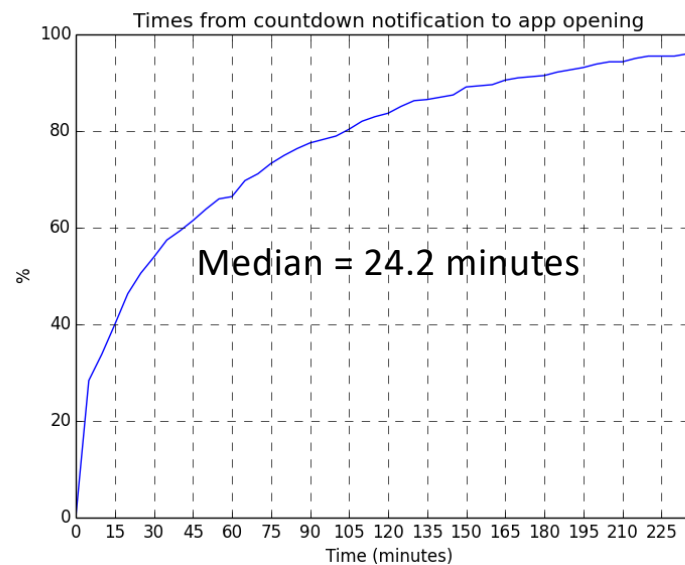
54% viewed within 30 minutes

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Mobile phone-based interventions for mental health: A systematic meta-review of 14 meta-analyses of randomized controlled trials

Simon B. Goldberg ✉, Sin U Lam, Otto Simonsson, John Torous, Shufang Sun

Article	Authors	Metrics	Comments	Media Coverage	Peer Review

⌄

- Abstract
- Method
- Results
- Discussion
- Supporting information
- Acknowledgments
- References

- Reader Comments
- Figures

Abstract

Mobile phone-based interventions have been proposed as a means for reducing the burden of disease associated with mental illness. While numerous randomized controlled trials and meta-analyses have investigated this possibility, evidence remains unclear. We conducted a systematic meta-review of meta-analyses examining mobile phone-based interventions tested in randomized controlled trials. We synthesized results from 14 meta-analyses representing 145 randomized controlled trials and 47,940 participants. We identified 34 effect sizes representing unique pairings of participants, intervention, comparisons, and outcome (PICO) and graded the strength of the evidence as using umbrella review methodology. We failed to find convincing evidence of efficacy (i.e., $n > 1000$, $p < 10^{-6}$, $I^2 < 50\%$, absence of publication bias); publication bias was rarely assessed for the representative effect sizes. Eight effect sizes provided highly suggestive evidence (i.e., $n > 1000$, $p < 10^{-6}$), including smartphone interventions outperforming inactive controls on measures of psychological symptoms and quality of life ($ds = 0.32$ to 0.47) and text message-based interventions outperforming non-specific controls and active controls for smoking cessation ($ds = 0.31$ and 0.19, respectively). The magnitude of effects and strength of evidence tended to diminish as comparison

Questions