# Mobile Health

# Lecture 12
# Mobile Devices and Behaviour Interventions

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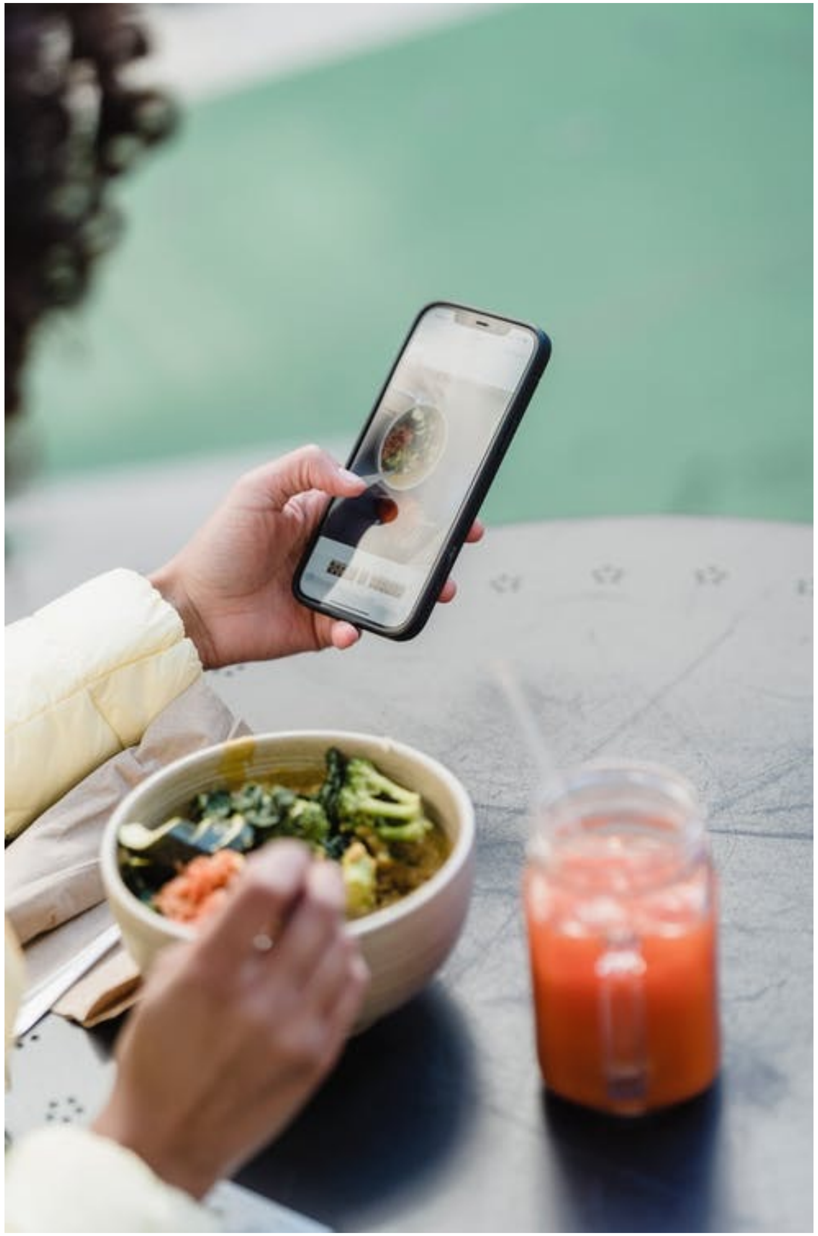
# Mobile Devices and Passive Sensing

- 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.

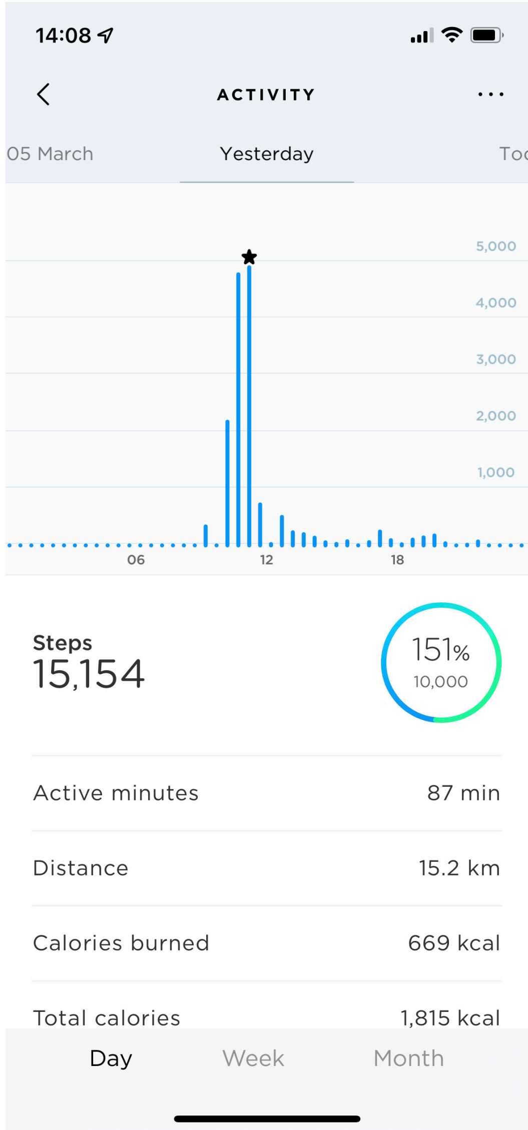


# What is a “digital intervention”?

- 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).
  - Help the person to not 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.

# Pull Interventions

- Interventions where it is the user who requests them.
- Example: someone going into an app to check how many steps they have done in a day.

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# Push Intervention

- A device prompting a user with a message


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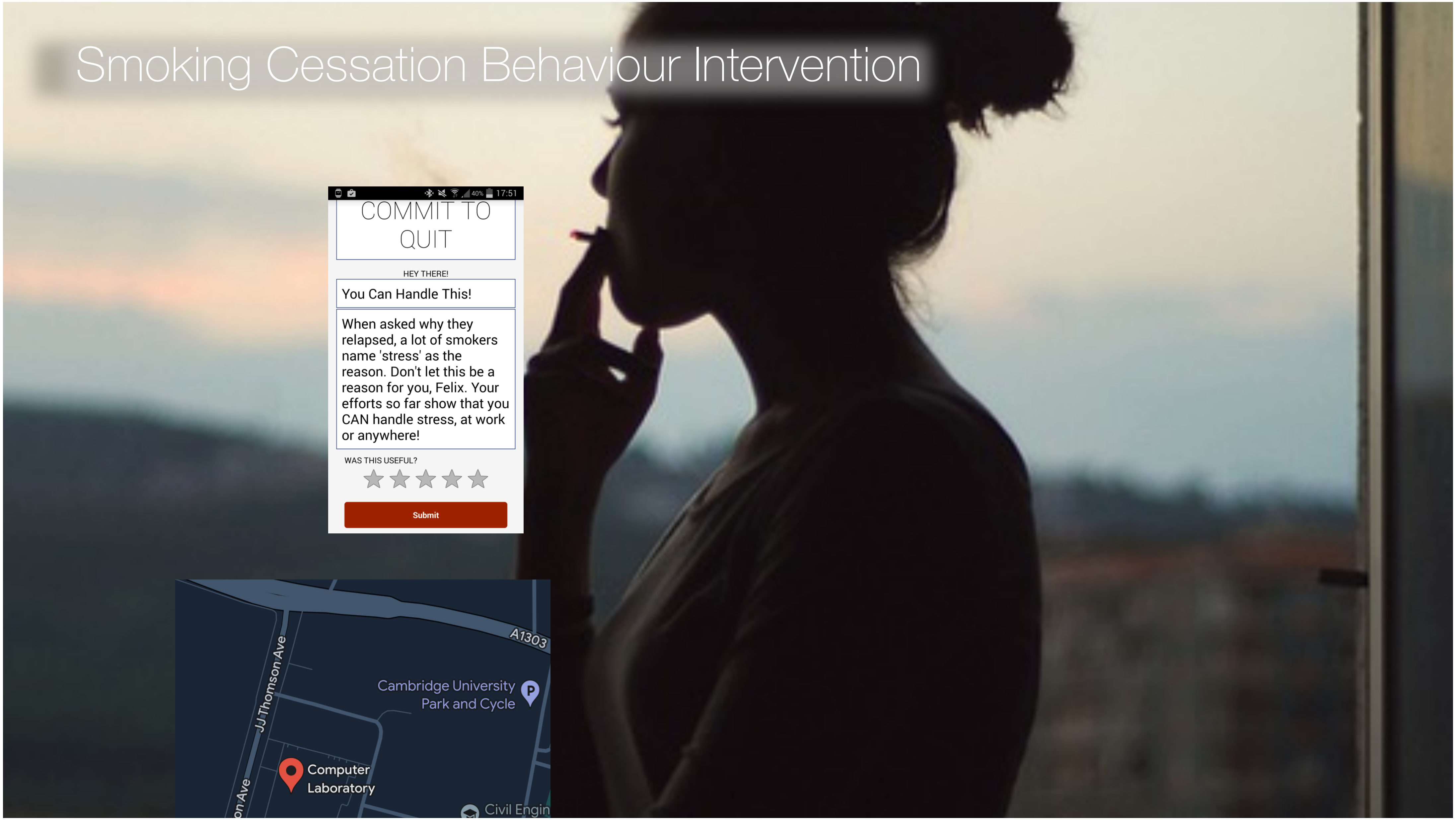
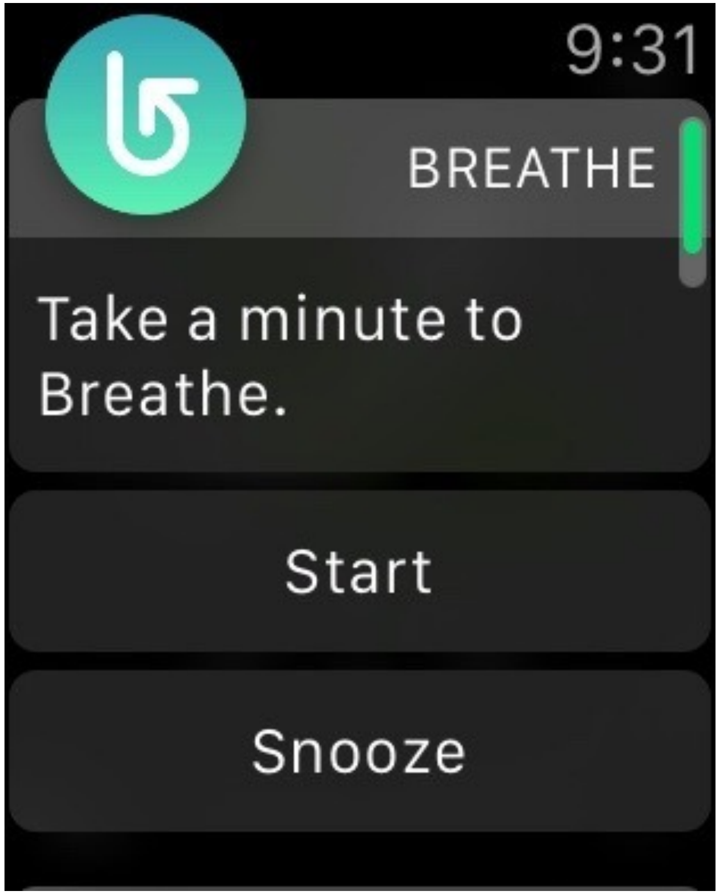

Smoking Cessation Behaviour Intervention
17:51
COMMIT TO QUIT
HEY THERE!
You Can Handle This!
When asked why they relapsed, a lot of smokers name 'stress' as the reason. Don't let this be a reason for you, Felix. Your efforts so far show that you CAN handle stress, at work or anywhere!
WAS THIS USEFUL?
Submit
A1303
JJ Thomson Ave
Cambridge University Park and Cycle
P
Computer Laboratory

# What form does a digital intervention take?

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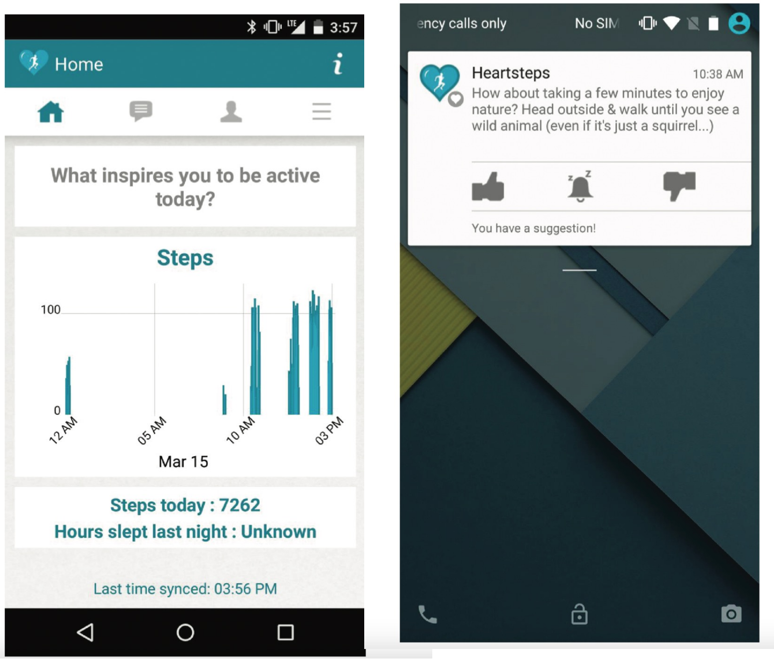
# Challenges

- 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).

Predrag Klasnja, PhD, Shawna Smith, PhD, Nicholas J Seewald, MS, Andy Lee, BS, Kelly Hall, BS, Brook Luers, MS, Eric B Hekler, PhD, Susan A Murphy, PhD, Efficacy of Contextually Tailored Suggestions for Physical Activity: A Micro-randomized Optimization Trial of HeartSteps, *Annals of Behavioral Medicine*, Volume 53, Issue 6, June 2019, Pages 573–582.

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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<br>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<br>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<br>Lunch<br>Midafternoon<br>Late afternoon | Weekdays<br>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 |

# 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,
  - Physiology.

# 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/activity/physiology.
- 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.

# 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 burdensome than another).
- Step count recorded in the 30 min following the randomization of suggestion delivery

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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.

# 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.

# RL Framework: Actions and Rewards

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

$At \in A$ (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.

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# 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

Reward of delivering a message is modelled by a feature vector considering previous dosage, app engagement and level of activity (f(s) measures that):

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

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.

An action A is drawn from a Bernoulli distribution.

η proxies long term effects of delivering a given the dosage treatment burden Xd
[probability is also clipped]

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

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# Action Planning

feature vector

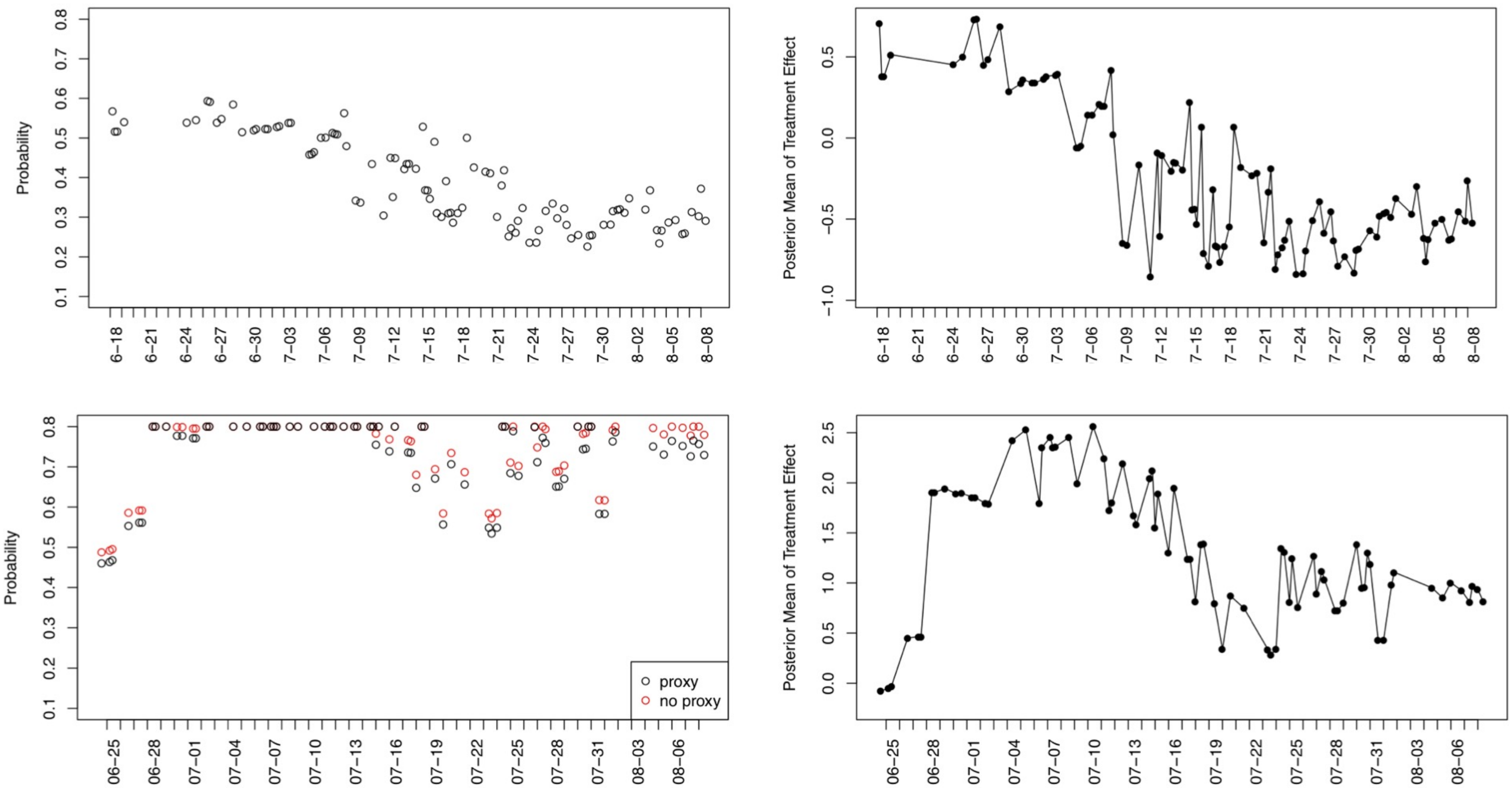
$$r_t(s,1) - r_t(s,0) = f(s)^\top \beta$$ → reward advantage

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

# 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 |

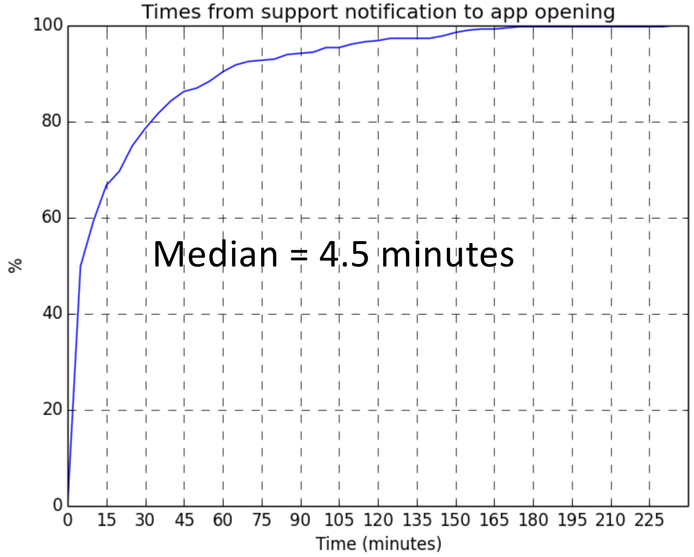
# Results: User 4 and User 7



# QuitSense: Smoke Cessation (Speed of) Engagement

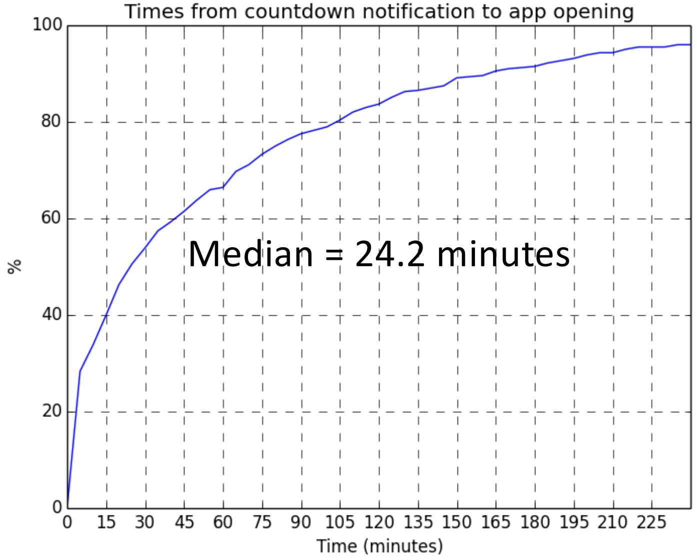
Median time to response after Geofenced Message notification (n=15) = 4.5 mins

**Geofence messages**




79% viewed within 30 minutes

**Daily support messages**




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

Published: January 18, 2022 • https://doi.org/10.1371/journal.pdig.0000002

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 (*d*s = 0.32 to 0.47) and text message-based interventions outperforming non-specific controls and active controls for smoking cessation (*d*s = 0.31 and 0.19, respectively). The magnitude of effects and strength of evidence tended to diminish as comparison

# Studies

**Table 1. Characteristics of included meta-analyses.**

| Meta-analysis | Population | Condition | Intervention | Outcomes | k | RoB | NIH |
|---|---|---|---|---|---|---|---|
| Cox (2020) [48] | adults | n/a | text messaging | depression | 9 | Cochrane, GRADE | 7 |
| Do (2018) [70] | adults/ adolescents | smoking | text messaging | smoking cessation | 6 | Cochrane | 8 |
| Firth (2017a) [38] | adults | mental health concerns | smartphone intervention | anxiety | 9 | Cochrane | 6 |
| Firth (2017b) [50] | adults | n/a | smartphone intervention | depression | 18 | Cochrane | 7 |
| Gál (2021) [39] | adults | n/a | meditation apps | anxiety, depression, stress, wellbeing | 34 | Cochrane | 7 |
| Gee (2016) [49] | adults/ adolescents | n/a | ecological momentary interventions | anxiety | 6 | Cochrane | 8 |
| Linardon (2019) [21] | adults/ adolescents | n/a | smartphone intervention | depression, anxiety, stress, quality of life | 66 | Cochrane | 6 |
| Linardon (2020) [71] | adults/ adolescents | n/a | smartphone app | self-compassion, mindfulness/acceptance, depression/distress | 33 | Cochrane | 7 |
| Scott-Sheldon (2016) [51] | adults | smoking | text messaging | smoking cessation | 16 | Jadad and other measures | 7 |
| Senanayake (2019) [72] | adults/ adolescents | depression | text messaging | depression | 7 | Joanna Briggs Institute | 7 |
| Spohr (2015) [52] | adults/ adolescents | smoking | text messaging | smoking cessation | 13 | n/a | 7 |
| Weisel (2019) [20] | adults | mental health concerns | smartphone app | depression, anxiety, suicidal ideation, smoking/drinking | 16 | n/a | 7 |
| Whittaker (2016) [37] | adults/ adolescents | smoking | text messaging / smartphone app | smoking cessation | 12 | Cochrane, GRADE | 7 |
| Whittaker (2019) [27] | adults/ adolescents | smoking | text messaging / smartphone app | smoking cessation | 17 | Cochrane, GRADE | 8 |

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# Effect Size

- Effect Size measures the effect of the treatment between the treated and control group.
- Cohen's d:

$$\frac{\text{Mean of treated group} - \text{Mean of control group}}{\text{SD of entire sample}}$$

# Effect Size on Existing Trials

**Table 2. Representative effect sizes across PICO categories.**

| Out | Pop | Cond | Intervention | Comp | Meta-analysis | k | n | ES | CI | $I^2$ | Pub | Strength |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anx | adult | n/a | smartphone | inactive | Linardon (2019) | 28 | 3,093 | 0.32 | [0.19, 0.44] | 63 | n/a | high suggest |
| Anx | adult | ↑ sx | smartphone | inactive | Firth (2017a) | 6 | 1,212 | 0.45 | [0.30, 0.61] | 32.4 | n/a | high suggest |
| Anx | adult | ↑ sx | app | inactive | Weisel (2019) | 6 | 806 | 0.49 | [0.27, 0.71] | 47 | n/a | weak |
| Anx | adult | n/a | med app | inactive | Gál (2021) | 10 | 1,381 | 0.31 | [0.17, 0.46] | 48 | n/a | suggestive |
| Anx | mix | n/a | EMA | non-specific | Gee (2016) | 6 | 1,021 | 0.31 | [0.07, 0.55] | 17.78 | yes | weak |
| Anx | adult | ↑ sx | app | non-specific | Weisel (2019) | 8 | 948 | 0.43 | [0.19, 0.66] | 66 | n/a | weak |
| Anx | adult | anxious | app | non-specific | Weisel (2019) | 4 | 479 | 0.3 | [-0.10, 0.70] | 75 | n/a | non-sig |
| Anx | adult | ↑ sx | smartphone | active | Firth (2017a) | 5 | 1,026 | 0.19 | [0.07, 0.31] | 0 | n/a | weak |
| Anx | adult | n/a | smartphone | active | Linardon (2019) | 8 | 890 | 0.18 | [0.07, 0.29] | 7 | n/a | weak |
| Anx | adult | n/a | med app | specific | Gál (2021) | 4 | 337 | 0.26 | [-0.00, 0.52] | 0 | n/a | non-sig |
| Anx | adult | n/a | smartphone | specific | Linardon (2019) | 4 | 246 | 0.09 | [-0.21, 0.39] | 32 | n/a | non-sig |
| Dep | adult | n/a | med app | inactive | Gál (2021) | 8 | n/a | 0.35 | [0.24, 0.47] | 9 | n/a | weak |
| Dep | adult | n/a | smartphone | inactive | Linardon (2019) | 34 | 3,907 | 0.32 | [0.22, 0.42] | 52 | n/a | high suggest |
| Dep | adult | n/a | text | non-specific | Cox (2020) | 9 | 1,918 | 0.27 | [0.00, 0.54] | 82.5 | n/a | weak |
| Dep | mix | n/a | smartphone | non-specific | Linardon (2019) | 8 | 1,840 | 0.39 | [0.21, 0.58] | 60 | n/a | suggestive |
| Dep | adult | ↑ sx | app | non-specific | Weisel (2019) | 12 | 1,544 | 0.34 | [0.18, 0.49] | 53 | n/a | suggestive |
| Dep | adult | depressed | app | non-specific | Weisel (2019) | 6 | 796 | 0.33 | [0.10, 0.57] | 59 | n/a | weak |
| Dep | adult | n/a | smartphone | active | Firth (2017b) | 12 | 2,381 | 0.22 | [0.10, 0.33] | 47.2 | no | suggestive |
| Dep | adult | n/a | med app | specific | Gál (2021) | 5 | 981 | 0.28 | [0.09, 0.48] | 0 | n/a | weak |
| Dep | adult | n/a | smartphone | specific | Linardon (2019) | 12 | 751 | 0.13 | [-0.07, 0.34] | 60 | n/a | non-sig |
| Dep | adult | n/a | smartphone | adjunct | Linardon (2019) | 4 | n/a | 0.26 | [-0.09, 0.61] | 71 | n/a | non-sig |
| Smoke | mix | smokers | mobile | non-specific | Whittaker (2016) | 12 | 11,885 | 0.3 | [0.22, 0.38] | 59 | n/a | high suggest |
| Smoke | mix | smokers | text | non-specific | Whittaker (2019) | 13 | 14,133 | 0.31 | [0.24, 0.38] | 71 | n/a | high suggest |
| Smoke | adult | smokers | text | active | Scott-Sheldon (2016) | 16 | 19,364 | 0.19 | [0.14, 0.24] | n/a | n/a | high suggest |
| Smoke | adult | smokers | text | adjunct | Whittaker (2019) | 4 | 997 | 0.31 | [0.08, 0.54] | 0 | n/a | weak |
| SU | adult | ↑ sx | app | non-specific | Weisel (2019) | 5 | 1,732 | 0.18 | [-0.09, 0.45] | 81 | n/a | non-sig |
| Stress | adult | n/a | smartphone | inactive | Linardon (2019) | 20 | 2,558 | 0.47 | [0.33, 0.62] | 60 | n/a | high suggest |
| Stress | adult | n/a | med app | inactive | Gál (2021) | 8 | 923 | 0.62 | [0.24, 1.01] | 80 | n/a | weak |
| Stress | adult | n/a | smartphone | active | Linardon (2019) | 6 | 929 | 0.09 | [-0.05, 0.24] | 0 | n/a | non-sig |
| SI | adult | ↑ sx | app | non-specific | Weisel (2019) | 4 | 286 | 0.14 | [-0.10, 0.37] | 0 | n/a | non-sig |
| QOL | mix | n/a | smartphone | inactive | Linardon (2019) | 37 | 4,672 | 0.35 | [0.28, 0.43] | 29 | n/a | high suggest |
| QOL | adult | n/a | smartphone | non-specific | Linardon (2019) | 4 | 489 | 0.41 | [0.21, 0.61] | 0 | n/a | weak |
| QOL | adult | n/a | smartphone | specific | Linardon (2019) | 6 | 388 | 0.02 | [-0.14, 0.17] | 0 | n/a | non-sig |
| WB | adult | n/a | med app | non-specific | Gál (2021) | 4 | n/a | 0.31 | [0.05, 0.56] | 0 | n/a | weak |

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**ARTICLE** OPEN

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# Wearable technology interventions in patients with chronic obstructive pulmonary disease: a systematic review and meta-analysis

Amar J. Shah[1,2], Malik A. Althobiani[2,3], Anita Saigal[1,2], Chibueze E. Ogbonnaya[4], John R. Hurst[1,2] and Swapna Mandal[1,2]✉

Chronic obstructive pulmonary disease (COPD) is the third leading cause of death and is associated with multiple medical and psychological comorbidities. Therefore, future strategies to improve COPD management and outcomes are needed for the betterment of patient care. Wearable technology interventions offer considerable promise in improving outcomes, but prior reviews fall short of assessing their role in the COPD population. In this systematic review and meta-analysis we searched ovid-MEDLINE, ovid-EMBASE, CINAHL, CENTRAL, and IEEE databases from inception to April 2023 to identify studies investigating wearable technology interventions in an adult COPD population with prespecified outcomes of interest including physical activity promotion, increasing exercise capacity, exacerbation detection, and quality-of-life. We identified 7396 studies, of which 37 were included in our review. Meta-analysis showed wearable technology interventions significantly increased: the mean daily step count (mean difference (MD) 850 (494–1205) steps/day) and the six-minute walk distance (MD 5.81 m (1.02–10.61 m). However, the impact was short-lived. Furthermore, wearable technology coupled with another facet (such as health coaching or pulmonary rehabilitation) had a greater impact that wearable technology alone. Wearable technology had little impact on quality-of-life measures and had mixed results for exacerbation avoidance and prediction. It is clear that wearable technology interventions may have the potential to form a core part of future COPD management plans, but further work is required to translate this into meaningful clinical benefit.

*npj Digital Medicine* (2023)6:222 ; https://doi.org/10.1038/s41746-023-00962-0

# Questions

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