Steps towards digital tools for personalised physical activity promotion

David E Conroy ,[1,2] Gary G Bennett,[3] Constantino M Lagoa,[4] Kathleen Y Wolin[5]

Digital health has grown from a collection of provocative ideas into a multibillion-dollar industry in just over a decade in part because of the promise of this technology for improving physical activity monitoring and promotion strategies. Systematic reviews and meta-analyses of evidence for this technology are beginning to accumulate.[1 2] In this commentary, we offer some important considerations as the field moves towards creating personalised strategies for promoting physical activity.

First, apps and wearable trackers are often portrayed as tools for promoting physical activity, but, by themselves, they are not treatments. They are simply vehicles for delivering the psychologically active ingredients of behaviour change, akin to the capsule that encloses pharmacologically active agents in medication. Physicians do not prescribe medication based on the delivery vehicle alone; they consider the mechanism of dysfunction to target, active ingredients in the drug and dosing to inform treatments. It is inappropriate to conclude that digital tools promote positive changes in activity; poorly designed interventions deployed via digital modes are no more than a digital placebo—they lack a defined target or active ingredient but are delivered in a shiny new capsule.

Second, between-group differences in treatment and control groups are the *sine qua non* of randomised clinical trials, but they are not the only important source of evidence. Randomised clinical trial designs are privileged as the gold-standard for causal inferences in evidence-based medicine. Yet they create a vulnerability to the ecological fallacy. Patterns of interindividual variation would only be expected to generalise to intraindividual variation under very stringent conditions that are unlikely to be met in the real world.[3] Behaviour change is fundamentally an intraindividual (within-person) phenomenon. It cannot be properly understood without a clear understanding of within-person processes. Growing interest in ecological momentary assessment and N-of-1 designs for physical activity signals awareness of the need to focus on intra-individual change.[4 5] But this interest has had limited impact on physical activity intervention design. That must change if we are to improve population health and our understanding of behaviour change dynamics.

Third, effect sizes need to be interpreted and communicated carefully to avoid creating hype and unrealistic expectations. One recent review sparked eye-catching international headlines that apps and wearable trackers increased physical activity by 1850 steps/day.[1] A closer look revealed that this estimate was the product of (a) a back-calculated standard deviation from studies that used steps as an outcome and (b) a standardised difference in means from studies using either steps or physical durations as an outcome. Only four of the 21 studies with steps as an outcome reported a difference in means greater than the 1850 steps/day threshold. Three of those four studies had N≤32, and the four samples represented just 3.2% of the overall sample size in the 21 studies. The average difference in group means, 753 steps/day, was less than half what headlines proclaimed. That value is closer to the 950 steps/day difference between groups receiving Fitbit-based interventions and control groups in a similar but independent meta-analysis around the same time.[2] Liberal assumptions based on small studies are not needed to build enthusiasm for digital health. It confuses understanding and will hinder long-term advances.

Fourth, personalisation refers to a type of experience rather than a specific strategy or technique. In their recent review of the effects of apps and wearable trackers on physical activity, Laranjo *et al* reported that interventions with personalisation features had larger effects than those without those features.[1] In those studies, personalisation was almost entirely based on

[1]Kinesiology, The Pennsylvania State University, University Park, Pennsylvania, USA
[2]Preventive Medicine, Northwestern University Feinberg School of Medicine, Chicago, Illinois, USA
[3]Psychology and Neuroscience, Duke University, Durham, North Carolina, USA
[4]School of Electrical Engineering and Computer Science, The Pennsylvania State University, University Park, Pennsylvania, USA
[5]Circea, LLC, Chicago, Illinois, USA

Correspondence to Dr David E Conroy, Kinesiology, The Pennsylvania State University, University Park, PA 16802, USA; conroy@psu.edu

behavioural interventions that customised messages with a user's name; some incorporated content that was relevant to a specific subpopulation (ie, targeting). More recently, just-in-time adaptive interventions apply decision algorithms that tailor intervention delivery to individuals' moments of receptivity, opportunity or vulnerability.[6] Efforts are now underway to statistically optimise decision rules for both populations (using reinforcement learning) and individuals (using control systems engineering).[7] Based on the diversity of these approaches, claims that an intervention is personalised reveals very little because the techniques that create a personalised experience are not exchangeable and may have different effects on behaviour change. Personalisation is not an active ingredient for behaviour change—it is a suite of strategies for adapting the targets, active ingredients, doses and modes of intervention in different contexts to create a desired experience.

Of course, the overarching question we really need to ask is whether more personalisation necessarily produces better outcomes. Might it be enough to simply convince users that their intervention experience is personalised to keep them engaged and achieve intervention goals?[8] Until we answer that question, we should be careful to specify and differentiate between personalisation strategies.

A new science of personalised behaviour change is on the horizon thanks to advances in digital health. Physical activity provides a compelling use case to lead that work if we can resist the temptation to overstate the evidence, and instead move towards greater specificity of targets, active ingredients, dosing and rules for adapting interventions based on contexts and individual differences.

Twitter David E Conroy @conroylab

Contributors All authors contributed to the conceptualisation of this editorial. DEC wrote the original draft. All authors contributed to the revision and approval of the final draft.

Funding DEC and CML were supported by the National Heart, Lung, and Blood Institute of the National Institutes of Health under Award Number R01HL142732, and the National Science Foundation under Award Number ECCS1808266.

Disclaimer The content is solely the responsibility of the authors and does not necessarily represent the official views of either the National Institutes of Health or the National Science Foundation.

Competing interests GGB holds equity in Coeus Health and serves on the scientific advisory boards of WW, Gelesis and Naturally Slim. KYW holds equity in Coeus Health. These organisations had no writing this editorial, or in the decision to submit the article for publication.

Patient consent for publication Not applicable.

Provenance and peer review Not commissioned; externally peer reviewed.

To cite Conroy DE, Bennett GG, Lagoa CM, *et al*. *Br J Sports Med* 2022;**56**:424–425.

Accepted 3 August 2021
Published Online First 16 September 2021

Br J Sports Med 2022;**56**:424–425.
doi:10.1136/bjsports-2021-104169

ORCID iD
David E Conroy http://orcid.org/0000-0003-0204-4093

REFERENCES

1 Laranjo L, Ding D, Heleno B, *et al*. Do smartphone applications and activity trackers increase physical activity in adults? systematic review, meta-analysis and metaregression. *Br J Sports Med* 2021;55:422–32.
2 Ringeval M, Wagner G, Denford J, *et al*. Fitbit-Based interventions for healthy lifestyle outcomes: systematic review and meta-analysis. *J Med Internet Res* 2020;22:e23954.
3 Molenaar PCM. A manifesto on psychology as idiographic science: bringing the person back into scientific psychology, this time forever. *Measurement* 2004;2:201–18.
4 McDonald S, Quinn F, Vieira R, *et al*. The state of the art and future opportunities for using longitudinal N-of-1 methods in health behaviour research: a systematic literature overview. *Health Psychol Rev* 2017;11:307–23.
5 Dunton GF, Rothman AJ, Leventhal AM, *et al*. How intensive longitudinal data can stimulate advances in health behavior maintenance theories and interventions. *Transl Behav Med* 2021;11:281–6.
6 Nahum-Shani I, Smith SN, Spring BJ, *et al*. Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Ann Behav Med* 2018;52:446–62.
7 Conroy DE, Lagoa CM, Hekler E, *et al*. Engineering person-specific behavioral interventions to promote physical activity. *Exerc Sport Sci Rev* 2020;48:170–9.
8 Li C. When does web-based personalization really work? the distinction between actual personalization and perceived personalization. *Comput Human Behav* 2016;54:25–33.