Tailored goals and individual choice: A field experiment on automated commitment devices for health behavior

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Abstract

The incidence of chronic diseases associated with physical inactivity is on the rise. To address this public health issue we developed a mobile app that utilizes contextual multi-armed bandits, a type of reinforcement learning algorithm, to develop personalized workout plans, adjusting task difficulty. To test the role of tailoring and choice, we develop an adaptive intervention to measure the effectiveness of personalized goal recommendation (varying task difficulty) based on online reinforcement learning. Participants are divided into three groups: user choice (no recommendation), user choice with automated recommendations (contextual bandits), and automated plans without choice (contextual bandit optimal action). The main objectives are (1) to determine the effectiveness of contextual bandits for automated goal setting, (2) to understand the role of user characteristics impacting ideal workout schedules, and (3) to explore the influence of user autonomy on recommendation effectiveness. This research will contribute to the understanding of user choice versus data-driven recommendations in mobile health interventions, potentially informing the development of more effective behavior-change apps.

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Abstract

The incidence of chronic diseases associated with physical inactivity is on the rise. To address this public health issue we developed a mobile app that utilizes contextual multi-armed bandits, a type of reinforcement learning algorithm, to develop personalized workout plans, adjusting task difficulty. In this field adaptive experiment we investigate the effectiveness of goal recommendation (task difficulty) based on reinforcement learning. Participants are divided into three groups: user choice (no recommendation), user choice with automated recommendations (contextual bandits), and automated plans without choice (contextual bandit optimal action). The main objectives are (1) to determine the effectiveness of contextual bandits for automated goal setting, (2) to understand the role of user characteristics impacting ideal workout schedules, and (3) to explore the influence of user autonomy on recommendation effectiveness. This research will contribute to the understanding of user choice versus data-driven recommendations in mobile health interventions, potentially informing the development of more effective behavior-change apps.

Keywords: Contextual Bandits, Physical Activity Promotion, Behavior Change Interventions, Adaptive Experimentation, Personalized Exercise, Machine Learning, User Autonomy

1 Introduction

Regular physical activity (PA) is essential for maintaining overall health and wellbeing [1]. Extensive research has demonstrated that consistent exercise is associated with numerous health benefits, including improved sleep quality, enhanced mood, and a reduced risk of noncommunicable chronic diseases (NCDs) such as diabetes, stroke, depression, and dementia. In contrast, physical inactivity has been identified as one of the leading risk factors for premature mortality and a significant contributor to the rising healthcare costs [2–4]. Despite the well-documented benefits of PA and risks associated with a sedentary lifestyle, 31 percent of the global adult population—equivalent to 1.8 billion adults—fail to meet the recommended levels of physical activity [5]. Even with unwavering global efforts from national and international policy, mass media campaigns, to social support and educational programs [6], the number of adults who are physically inactive has been steadily increasing in high income countries [7].

To address this public health issue, researchers have designed and implemented various interventions aimed at promoting regular exercise adherence, many of which are based on prominent social and psychological theories [8, 9], such as theory of planned behavior [10] or self-determination theory [11]. Although these interventions have shown promise in increasing individuals' intentions to engage in physical activity, a key challenge lies in translating these intentions into sustained behavior [12, 13]. This discrepancy is known as the 'intention-behavior gap', emphasizing that goal intentions only partially materialize on corresponding actions [14]. Studies indicate that individual factors such as lack of motivation and low self-efficacy, as well as environmental barriers, such as time constraints, can hinder individuals from acting on their intentions, even when they recognize the benefits of physical activity [13, 15]. Moreover, these factors are highly heterogeneous across individuals and time. Thus, addressing these challenges requires individualized, flexible, and engaging interventions that consider individual needs, preferences, and contexts, and which promote self-efficacy, and focus on closing the intention-behavior gap.

Mobile phone applications, commonly referred as ”apps”, have emerged as promising platforms for delivering effective health interventions, owing to widespread technological access and potential for personalization or tailoring [16]. While the overall evidence on the effectiveness of app-based mHealth interventions on PA engagement is mixed [17–19], interventions that allow for tailoring, especially considering changes in context over time, show promising results [16]. For example, a study in 2006 demonstrated that computer-tailored interventions, which provide personalized feedback and actionable recommendations, significantly increased physical activity levels among participants compared to generic advice [20]. Similarly, researchers in 2011 found that interventions incorporating goal-setting, self-monitoring, and personalized planning were more effective in promoting sustained behavior change [21]. These approaches recognize that a ”one-size-fits-all” strategy is often insufficient, as individuals face unique challenges such as time constraints, lack of social support, or low self-efficacy. By addressing these barriers through tailored solutions, such as adaptive goal-setting, context-specific reminders, or individualized support systems, interventions can better align with participants' lifestyles and enhance their ability to act on their intentions.

The taxonomy of personalization features is extensive, as apps allow for datadriven mechanisms which can respond to user behavior and real-time context, delivering messages, adapting user experience, tailoring interactions with other participants, providing user targeting, among other features [22]. However, in most applications, personalization is designed to increase user engagement with the app rather than focusing on sustained behavior adoption [23], in most cases due to a lack of theoretical framework [24]. Evidence from behavioral models, such as the Integrated Behavior Change (IBC) model [25, 26], propose that behavior adoption can be measure as the success in completing of a sequence of goals (i.e. plans) over time (Figure 1). Therefore, app features should focus on tailoring goals (adapting their difficulty, for example) in order to maximize the likelihood of goal completion, acknowledging time-variant factors (or contexts) that can affect individuals in a daily basis, as well as time-invariant aspects that could vary dramatically across users. Earlier work on message tailoring has suggested that including elements of multiple dominant psychological theories into tailoring approaches increases overall effectiveness [27], suggesting the IBC model is well-suited for developing tailoring approaches.

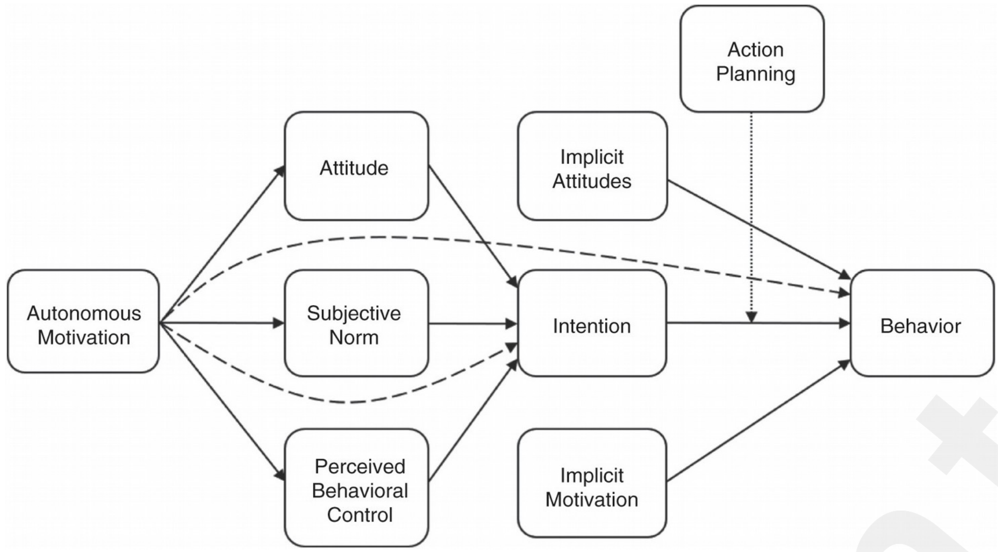

Fig. 1 Integrated behavioral change model (Hagger et al., 2020).

With the technological advances in artificial intelligence, personalization has become easier to implement in dynamic settings, where users are interacting repeatedly with tailored components. In particular, contextual multi-armed bandits, or simply contextual bandits (CB), have become an effective reinforcement (machine) learning personalization tool in the health behavior domain, where treatment (option) recommendations are optimally determined to maximize user's performance using individual characteristics and behavior [28]. In short, CB algorithms use all available data to predict the action that would provide the best outcome to a given user, while learning from the relative performance of all possible actions. In the experimental literature, there is a novel approach using CB, named adaptive interventions, emphasizing the idea that we can pose a field experiment with an adaptive sampling procedure that aims to determine which types of individuals benefit from certain intervention arms over time, while also learning about the average effectiveness of each arm [29, 30]. Adaptive interventions allow to understand the effectiveness of different strategies, while providing context-based personalization. Overall, CB has important advantages as an automated personalization tool; it requires less data to determine which interventions are more effective overall, and it allows to understand which characteristics are most likely to influence individuals' performance.

Adaptive interventions using CB algorithms have become popular in the public health domain, with promising results [16, 22, 31]. Systematic reviews for adaptive interventions targeting PA and sedentary behavior reveal that most studies focus on tailored feedback as the main personalization component, with few interventions focusing on goal tailoring. Moreover, adaptive experiments with goal setting features either on progression, i.e. increasing difficulty over time [22] or alternating types of exercises (e.g. cardio, strenght, flexibility) based on user health profile. Yet, to date is still unclear to which extent automated personalized goal difficulty recommendations and individual preferences influence the effect of goals as plans (namely commitment devices) towards health behavior adoption.

This study explore three research questions to evaluate the effectiveness of adaptive interventions that focus on goal difficulty and user choice:

1. Can contextual bandits outperform performance success rate (goal completion) relative to user-chosen workouts?
2. Which user characteristics are most relevant for determining choice probabilities among intervention arms?
3. To what extent does user autonomy in choosing a workout plan influence the effectiveness of

recommendations based on contextual bandits?

By addressing these questions, this experiment aims to contribute to the growing body of research on adaptive behavior change interventions. Understanding the interplay between user choice and data-driven recommendations can inform the development of more effective mobile health (mHealth) applications [32].

2 Methods

2.1 Contextual bandits algorithm

The contextual multi-armed bandit model is a type of reinforcement machine learning approach, which uses experimentation to learn about users performance and recommend best potential option. As shown in Figure 2, the algorithm incorporates users' past outcomes (target) and context (features) to assign probabilities to each treatment option and recommend the best possible treatment in the future (higher likelihood of success, noted in green). Once given a recommendation, users respond (either positively or negatively in this case), and this information is used to further training the algorithm for the next interaction. There are several algorithm developed to solve CB models, differing in how probabilities for each option are updates (learning) and also the degree of exploration (randomness) involved in providing users with different options.

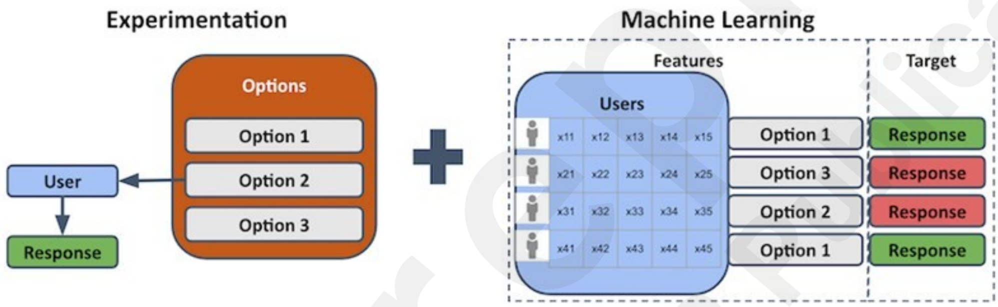

Fig. 2 Contextual bandit algorithm design (adapted from Ambiata ©).

Formally, at each round $t = 1,...,T$, we observe the individual's context ($x_t \in X$), from which the algorithm recommends an action ($a_t \in A$), and the environment reveals a reward ($r_t \in [0,1]$). Intuitively, the algorithm needs to choose the policy $\pi \in \Pi$ that maximizes the cumulative reward, where Π is a mapping of all policies relating context to actions ($\Pi \subseteq \{X \rightarrow A\}$). We can define the average reward of a policy π as:

$$V(\pi) = \frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[r_t \mid x, \pi(x)]$$

Based on this idea of expected reward, we can then determine the cumulative regret from a given policy, as the difference between the reward of the chosen action and the expected reward of the recommended action:

$$\text{Regret} = \left(\sum_{t=1}^{T} r_t(\pi(x_t))\right) - \sum_{t=1}^{T} r_t \quad \max{}_{\pi\in\Pi}$$

In this setup, contextual bandit (CB) algorithms differ in their proposed approaches to achieve regret minimization. In practice, some algorithms will be better suited for different empirical applications, depending on the number of rounds, the possible set of actions, and the heterogeneity in the context from which the algorithm learns to allocate the best recommendation. As such, the pilot phase is critical to determining the best approach for this experiment.

2.2 Integrated Behavior Change Model

The project adopts the Integrated Behavior Change (IBC) Model for physical activity [25] as a framework for tailoring workout difficulty recommendations (i.e. goals). By leveraging the IBC model, the app ensures that its recommendations address not only the physical aspects of exercise but also the psychological factors that influence behavior change. In particular, we capture data on the psychological constructs defined in the IBC model, which are later used as contexts for the algorithm learning process. Moreover, in order to directly test the role of choice autonomy, the experimental design contrasts three methods for presenting workout plans:

- Choice-Driven: Users select their desired workout difficulty level from a predefined menu. This approach provides users with a sense of autonomy and control over their exercise routine. Choice-driven tailoring leaves the selection of the intervention to the user, allowing individuals to reveal their preferences in a participatory process [33].

- Data-recommended: The CB algorithm determines optimal workout difficulty (based on the user data and IBC model), and provides a recommendation to the user but it retains the option to choose an alternative. This design allows us to investigate the interplay between user autonomy and the effectiveness of datadriven recommendations [27].

- Data-Driven: The CB algorithm automatically recommends workouts based on user data, including contextual features based on the IBC model. This method leverages a machine learning approach to personalize workout plans and potentially optimize user performance (measured as goal completion).

By comparing these three approaches, the project aims to identify the optimal balance between user choice and automated guidance in promoting physical activity through mobile technology.

2.3 Study Design

Participants will be randomly assigned to one of three groups:

1. Random Recommendations: Represents a choice-driven approach where participants select their own fitness challenges.
2. Automated Recommendations: Leverages contextual bandits (CB) to personalize workout plans based on individual performance and context.
3. Automated Goals: Similar to automated recommendations but eliminates user choice by assigning goals directly.

Randomization will be stratified by baseline demographic factors, including age and gender, to ensure balanced representation across groups. This two-phase adaptive experiment will begin with a pilot study to optimize the contextual bandit algorithm, followed by the main experiment to evaluate intervention effectiveness. The inclusion criteria require participants to be physically healthy adults, with access to a smartphone compatible with the mobile app. Exclusion criteria include significant physical disabilities or medical conditions limiting exercise, as well as individuals actively participating in competitive sports. Randomization will employ block randomization to reduce bias and ensure even group distribution, with allocations concealed from both participants and researchers through a secure digital system. The study is organized in two phases:

2.3.1 Phase 1: Pilot Study

- **Purpose:** Train and optimize the contextual bandit algorithm.
- **Sample Size:** 1,000 participants across multiple university settings.
- **Duration:** Two rounds of three days each (with a rest day).
- **Procedures:**

  - Participants complete a baseline survey eliciting the IBC model
  - Randomly assigned goals in round 1 (among three difficulty levels).
  - CB algorithm determines goal assignment in round 2 based on performance data in round 1.
  - Incentives: Participants are compensated for their time during this phase.

2.3.2 Phase 2: Main Experiment

- **Purpose:** Evaluate intervention effectiveness across three arms:

  1. Self-set Goals: Participants choose their own goals.
  2. Automated Recommendations: Participants receive suggested goals but retain the option to choose.
  3. Automated Goals Without Choice: Goals are assigned directly by the algorithm.

- **Sample Size:** 500 participants across multiple university settings.
- **Duration:** 10 rounds with a rest day between rounds.
- **Procedures:**

  - Participants complete the baseline survey as in phase 1.
  - Assigned to one of the three groups, difficulty level is set based on data from round 1 (except for group with self-set goals).
  - Complete assigned or chosen fitness challenges for three consecutive days per round.
  - Data collected after each round to inform future recommendations.
  - Incentives: Participants are compensated for their time and receive points for completed goals (increasing with difficulty) which factor into a chance to win prizes through a lottery at the end of the study.

The sample sizes of 1,000 (for phase one) and 500 participants (for phase two) was determined via power analysis, considering the particularities of adaptive experiment design. Simulations based on the relevant populations were conducted in order determine optimal policy learning using the epsilon-greedy algorithm. Based on simulated data, the sample size is sufficient to evaluate differences between intervention arms and conduct statistical inference, particularly regarding demographic and behavioral characteristics between participants.

The proposed app and study design was developed in order to experimentally evaluate the role of autonomy and motivation on goal setting and competition, thus removing randomization other important aspects of tailoring (e.g. motivational messages). However, best practices were taken into consideration to incorporate multiple personalization aspects (e.g. feedback, user targeting, group interaction), in order to maximize users' engagement during the experiment.

2.4 Data Collection

Data collection in this study spans multiple dimensions, capturing individual characteristics, app usage patterns, and most importantly, user performance. This multifaceted approach allows us provide insights on the potential heterogeneous impact of tailored goal-setting interventions.

- **Baseline Survey:** Participants will complete an online survey to gather demographic information (e.g., age, gender, socioeconomic status), fitness history (e.g., frequency and type of physical activity), and constructs from the Integrated Behavior Change (IBC) Model, such as perceived behavioral control, motivation types (autonomous and controlled), and self-regulatory capacities.
- **Fitness App Data:** The app will track participant engagement and outcomes, including goal completion rates, total time spent on physical activities, and engagement metrics (e.g., frequency of app interactions).
- **Algorithm Data:** The contextual bandit algorithm embedded in the app will collect data on contextual features (e.g., user preferences, past performance, fitness level) and reward functions to predict optimal goals and adapt recommendations over time.

2.5 Statistical Analysis

Statistical analysis will focus on comparing goal completion rates, engagement metrics, and user satisfaction across the three intervention groups. To address missing data, a multiple imputation approach will be applied to ensure robustness in outcome estimates. The primary analysis will estimate the conditional average treatment effect (CATE) for each intervention arm, with subgroup analyses to identify variations by demographics, baseline fitness, and psychological factors. Mixed-effects models will account for repeated measures and clustering within participants, while sensitivity analyses will assess the robustness of findings under varying assumptions.

- **Phase 1:** During the pilot phase, multiple contextual bandit (CB) algorithms will be evaluated based on metrics such as regret minimization (difference between actual and optimal rewards) and balance between exploration and exploitation.
- **Phase 2:** The main experiment will focus on estimating the CATE and analyzing differences in goal completion rates and engagement metrics.
- **Subgroup Analysis:** Subgroup analyses will explore how demographic characteristics (e.g., age, gender), motivational factors, and baseline fitness levels influence responsiveness.
- **Algorithm Evaluation:** Metrics such as cumulative reward, prediction accuracy, and contextual feature importance will be analyzed to evaluate the algorithm's ability to personalize recommendations effectively.

3 Results

This research is supported by the Fondecyt Initiation Grant 2024, under grant number ANID 11240325 (funding period 2024-2026). Recruitment is scheduled to begin in early 2025. We will begin data analysis once data collection is complete, which is planned to occur in fall 2025. We anticipate publishing the findings in 2026.

4 Discussion

This study introduces a novel approach to promoting sustained PA through a mobile app, leveraging CB learning for personalized goal difficulty recommendations, under a IBC framework. By combining this machine learning approach with a established PA behavioral model, the intervention addresses critical gaps in existing mHealth literature, particularly the role of autonomy and motivation on personalized goal setting. Findings from this field experiment will contribute to the growing field of adaptive digital health technologies, offering practical insights for scaling effective interventions for sustained health behavior. Ultimately, this research has the potential to inform public health strategies by providing evidence on the interplay between user autonomy and data-driven recommendations, fostering more engaging and effective health behavior change digital tools.

There are limitations to this study. First, participant dropout may introduce bias if attrition is non-random, and overall reduce statistical power. Our sample size considers a maximum 20 percent dropout rate, to maintain statistical validity. Secondly, findings may not generalize to populations of different ages, health status, those without smartphone access and from other cultural contexts beyond those included in the study. In a effort to provide better context, we implement this study in countries with different language and cultural background. Overall we believe that the proposed design can provide robust causal inference on the role of choice versus autonomy when tailoring goal difficulty is done under an adaptive data-driven approach.

The Ethics, Bioethics, and Biosafety Committee of the Vice Presidency of Research and Development at the University of Concepci´on has reviewed the PROJECT FONDECYT No. 11240325, titled *TAILORED GOALS VERSUS INDIVIDUAL CHOICE: A FIELD EXPERIMENT ON COMMITMENT DEVICES FOR HEALTH BEHAVIOR*, submitted in the FONDECYT INITIATION 2024 CALL by Dr. Juan Carlos Caro Seguel, as the Lead Researcher, a faculty member of the School of Engineering at the University of Concepci´on. The Committee has confirmed that it meets the ethical and bioethical standards and procedures established nationally and internationally for research involving human participation.

5 Acknowledgements

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6 Conflicts of Interest

None declared.

7 Abbreviations

CATE: conditional average treatment effect
CB: contextual bandits
IBC: Integrated Behavior Change
PA: physical activity
NCD: noncommunicable chronic disease

References

1. WHO. 2019. *Global action plan on physical activity 2018-2030: more active people for a healthier world*. World Health Organization.

2. Katzmarzyk, P.T. 2023. Expanding our understanding of the global impact of physical inactivity. *The Lancet Global Health 11*(1): e2–e3 .
3. Ding, D., K.D. Lawson, T.L. Kolbe-Alexander, E.A. Finkelstein, P.T. Katzmarzyk, W. Van Mechelen, and M. Pratt. 2016. The economic burden of physical inactivity: a global analysis of major non-communicable diseases. *The lancet 388*(10051): 1311– 1324 .
4. Katzmarzyk, P.T., C. Friedenreich, E.J. Shiroma, and I.M. Lee. 2022. Physical inactivity and non-communicable disease burden in low-income, middle-income and high-income countries. *British journal of sports medicine 56*(2): 101–106 .
5. Strain, T., S. Flaxman, R. Guthold, E. Semenova, M. Cowan, L.M. Riley, F.C. Bull, and G.A. Stevens. 2024. National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: a pooled analysis of 507 population-based surveys with 5· 7 million participants. *The Lancet Global Health 12*(8): e1232–e1243
.
6. Spring, B., A.C. Moller, and M.J. Coons. 2012. Multiple health behaviours: overview and implications. *Journal of public health 34*(suppl 1): i3–i10 .
7. Guthold, R., G.A. Stevens, L.M. Riley, and F.C. Bull. 2018. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 populationbased surveys with 1· 9 million participants. *The lancet global health 6*(10): e1077– e1086 .
8. Gourlan, M., P. Bernard, C. Bortolon, A.J. Romain, O. Lareyre, M. Carayol, G. Ninot, and J. Boich´e. 2016. Efficacy of theory-based interventions to promote physical activity. a meta-analysis of randomised controlled trials. *Health psychology review 10*(1): 50–66 .
9. Vasconcellos, D., P.D. Parker, T. Hilland, R. Cinelli, K.B. Owen, N. Kapsal, J. Lee, D. Antczak, N. Ntoumanis, R.M. Ryan, et al. 2020. Self-determination theory applied to physical education: A systematic review and meta-analysis. *Journal of educational psychology 112*(7): 1444 .
10. Ajzen, I. 1991. The theory of planned behavior. *Organizational behavior and human decision processes 50*(2): 179–211 .
11. Deci, E.L. and R.M. Ryan. 2000. The” what” and” why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological inquiry 11*(4): 227–268 .
12. Rhodes, R.E. and L. Dickau. 2012. Experimental evidence for the intention– behavior relationship in the physical activity domain: A meta-analysis. *Health Psychology 31*(6): 724 .
13. Rhodes, R.E. and G.J. de Bruijn. 2013. How big is the physical activity intention– behaviour gap? a meta-analysis using the action control framework. *British journal of health psychology 18*(2): 296–309 .
14. Sheeran, P. and T.L. Webb. 2016. The intention–behavior gap. *Social and personality psychology compass 10*(9): 503–518 .
15. Ghanvatkar, S., A. Kankanhalli, V. Rajan, et al. 2019. User models for personalized physical activity interventions: scoping review. *JMIR mHealth and uHealth 7*(1): e11098 .
16. Liu, X., N. Deliu, and B. Chakraborty. 2023. Microrandomized trials: developing just-in-time adaptive interventions for better public health. *American Journal of Public Health 113*(1): 60–69 .
17. Webb, T., J. Joseph, L. Yardley, S. Michie, et al. 2010. Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. *Journal of medical Internet research 12*(1): e1376 .

18. Gal, R., A.M. May, E.J. van Overmeeren, M. Simons, and E.M. Monninkhof. 2018. The effect of physical activity interventions comprising wearables and smartphone applications on physical activity: a systematic review and meta-analysis. *Sports medicine-open* 4: 1–15 .

19. Romeo, A., S. Edney, R. Plotnikoff, R. Curtis, J. Ryan, I. Sanders, A. Crozier, and C. Maher. 2019. Can smartphone apps increase physical activity? systematic review and meta-analysis. *Journal of medical Internet research 21*(3): e12053 .

20. Kroeze, W., A. Werkman, and J. Brug. 2006. A systematic review of randomized trials on the effectiveness of computer-tailored education on physical activity and dietary behaviors. *Annals of behavioral medicine 31*(3): 205–223 .

21. Williams, S.L. and D.P. French. 2011. What are the most effective intervention techniques for changing physical activity self-efficacy and physical activity behaviour—and are they the same? *Health education research 26*(2): 308–322 .

22. Monteiro-Guerra, F., O. Rivera-Romero, L. Fernandez-Luque, and B. Caulfield. 2019. Personalization in real-time physical activity coaching using mobile applications: a scoping review. *IEEE journal of biomedical and health informatics 24*(6): 1738–1751 .

23. Leong, U., B. Chakraborty, et al. 2023. Participant engagement in microrandomized trials of mhealth interventions: scoping review. *JMIR mHealth and uHealth 11*(1): e44685 .

24. Nahum-Shani, I., S.N. Smith, B.J. Spring, L.M. Collins, K. Witkiewitz, A. Tewari, and S.A. Murphy. 2018. Just-in-time adaptive interventions (jitais) in mobile health: key components and design principles for ongoing health behavior support. *Annals of behavioral medicine*: 1–17 .

25. Hagger, M.S. and N.L. Chatzisarantis. 2014. An integrated behavior change model for physical activity. *Exercise and sport sciences reviews 42*(2): 62–69 .

26. Hagger, M.S., L.D. Cameron, K. Hamilton, N. Hankonen, and T. Lintunen. 2020. *The handbook of behavior change*. Cambridge University Press.

27. Lustria, M.L.A., J. Cortese, S.M. Noar, and R.L. Glueckauf. 2009. Computertailored health interventions delivered over the web: review and analysis of key components. *Patient education and counseling 74*(2): 156–173 .

28. Tewari, A. and S.A. Murphy. 2017. From ads to interventions: Contextual bandits in mobile health. *Mobile health: sensors, analytic methods, and applications*: 495–517
.

29. Athey, S., K. Bergstrom, V. Hadad, J.C. Jamison, B. Ozler, L. Parisotto, and¨ J.D. Sama. 2023. Can personalized digital counseling improve consumer search for modern contraceptive methods? *Science Advances 9*(40): eadg4420 .

30. Deliu, N., J.J. Williams, and B. Chakraborty. 2024. Reinforcement learning in modern biostatistics: constructing optimal adaptive interventions. *International Statistical Review* .

31. Hardeman, W., J. Houghton, K. Lane, A. Jones, and F. Naughton. 2019. A systematic review of just-in-time adaptive interventions (jitais) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity* 16: 1–21 .

32. Mohr, D.C., M.N. Burns, S.M. Schueller, G. Clarke, and M. Klinkman. 2013. Behavioral intervention technologies: evidence review and recommendations for future research in mental health. *General hospital psychiatry 35*(4): 332–338 .

33. Lipman, S.A. 2024. One size fits all? designing financial incentives tailored to individual economic preferences. *Behavioural Public Policy 8*(2): 264–278 .

Supplementary Files

Multimedia Appendixes

IRB ethics review certificate.
URL: http://asset.jmir.pub/assets/4547206af00e94f3ff2c7ff11c4b0b1f.pdf

Informed consent form.
URL: http://asset.jmir.pub/assets/84371eee1e6fc471acf904e328cd611c.pdf