Feasibility Study

DIGITAL HEALTH

Digital Health
Volume 8: 1–13

DOI: 10.1177/20552076221115017
journals.sagepub.com/home/dhj
SAGE

A personalized mobile app for physical activity: An experimental mixed-methods study

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Abstract

Objectives: To investigate the feasibility of the be.well app and its personalization approach which regularly considers users' preferences, amongst university students.

Methods: We conducted a mixed-methods, pre-post experiment, where participants used the app for 2 months. Eligibility criteria included: age 18–34 years; owning an iPhone with Internet access; and fluency in English. Usability was assessed by a validated questionnaire; engagement metrics were reported. Changes in physical activity were assessed by comparing the difference in daily step count between baseline and 2 months. Interviews were conducted to assess acceptability; thematic analysis was conducted.

Results: Twenty-three participants were enrolled in the study (mean age = 21.9 years, 71.4% women). The mean usability score was 5.6 ± 0.8 out of 7. The median daily engagement time was 2 minutes. Eighteen out of 23 participants used the app in the last month of the study. Qualitative data revealed that people liked the personalized activity suggestion feature as it was actionable and promoted user autonomy. Some users also expressed privacy concerns if they had to provide a lot of personal data to receive highly personalized features. Daily step count increased after 2 months of the intervention (median difference = 1953 steps/day, p-value <.001, 95% CI 782 to 3112).

Conclusions: Incorporating users' preferences in personalized advice provided by a physical activity app was considered feasible and acceptable, with preliminary support for its positive effects on daily step count. Future randomized studies with longer follow up are warranted to determine the effectiveness of personalized mobile apps in promoting physical activity.

Keywords

Mobile applications [MeSH], exercise [MeSH], physical activity, health behavior [MeSH], personalization, tailoring, digital technology [MeSH]

Submission date: 29 June 2022; Acceptance date: 5 July 2022

Introduction

Early adulthood (defined as aged 18–34 years[1]), and the transition to university are often associated with reduced physical activity, with some evidence from systematic reviews suggesting a decline of 5 minutes/day in moderate-to-vigorous physical activity between adolescence and early adulthood.[2,3] Possible reasons for this decline could be major life changes associated with this period, such as starting university or employment, or moving out of home.[2,3] Health behaviors in early adulthood, such as physical activity

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patterns, tend to become habitual and persist into later adulthood,[4] with one in four adults being insufficiently active.[5] Given the link between regular physical activity and reduced mortality and morbidity,[6–13] it is crucial to target university students to increase their physical activity levels, and create long-term healthy habits.

Mobile apps are popular amongst young adults[14] and offer new possibilities to promote physical activity. To maximize their effects, mobile apps can include theory-based behavior change techniques, which are the active ingredients of an intervention, designed to alter causal processes that regulate behaviors.[15] Systematic reviews and randomized controlled trials have shown the effectiveness of some self-regulation and social behavior change techniques in increasing physical activity, namely self-monitoring, goal setting, feedback on behavior,[16,17] social support and social comparison.[18,19] Mobile apps can deliver self-regulation techniques seamlessly, by automatically collecting and displaying activity levels, and allowing users to set activity goals.[20,21] Additionally, mobile apps can also incorporate features of online social networks,[22,23] to facilitate social support or social comparison. To date, several meta-analyses have shown that mobile apps can effectively increase physical activity in the short term.[17,24] However, as many factors vary between people, and even within the same person over time,[25] research has suggested that a one-size-fits-all approach is insufficient, and personalized mobile apps can lead to greater physical activity increases, compared to non-personalized apps.[17,26,27]

Several meta-analyses suggest the positive effects of personalized mobile apps on physical activity;[17,26] however, a gap in the current personalization approach is the lack of users' preferences as input in the personalization algorithm.[26,28] Interviews with users have suggested that users want the personalization algorithms to *regularly* consider their preferences, and adapt to their changing needs and circumstances.[28,29] However, a recent systematic review including 31 personalized mobile apps found that only two physical activity apps collected and incorporated users' preferences in their personalization algorithm.[26] In these two interventions, users' preferences were often assessed at a single time point (e.g. baseline),[30,31] hence, missing the dynamic effects of time and context on user needs.[32]

To address this gap in the literature, we designed a physical activity mobile app (be.well) that collected users' preferences dynamically and incorporated them in the personalization algorithm to deliver activity suggestions. The be.well app included a "core" set of self-regulation and social behavior change techniques that have been shown to be effective in previous trials,[16–19] as well as this novel personalized feature.

Given that incorporating this personalized feature into a mobile app is a new approach, there is a need to understand the feasibility of this innovation. According to a widely used definition,[33,34] feasibility is the extent to which an innovation can be successfully used within a given context.

The main aim of this study is to investigate the feasibility of the be.well app and its personalization approach amongst university students, in the context of their day-to-day life (as opposed to in a clinical setting such as hospitals).

To get a comprehensive picture on feasibility assessment,[35,36] we examined the following aspects:

- Do people find the app usable? (assessed via a validated usability questionnaire)
- Do people use the app in their daily lives? (assessed via app engagement measures)
- Do people find the app acceptable? (assessed via post-intervention interviews)

If people do not use the app, or find it usable or acceptable, then it is unlikely that the approach is feasible and that the app will be adopted and moved to further testing for efficacy and effectiveness.[35,36] The secondary aim of this study is to assess preliminary effects on step count.

Methods

Study design

This was a mixed methods study of a quasi-experimental, pre-post design with one arm, where participants used a mobile app with a personalized feature for 2 months. The feasibility of the be.well app was assessed by app usage and post-intervention usability measures, intervention acceptability (via post-intervention interviews), and preliminary effects on daily step count. Ethics approval was granted by the Human Research Ethics Committee for Medical Sciences of Macquarie University (reference number: 52020638214729). The reporting follows the mobile health (mHealth) evidence reporting and assessment (mERA) checklist[37] (Supplemental Appendix 1), the transparent reporting of evaluations with non-randomized designs (TREND) statement[38] (Supplemental Appendix 2), and the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist[39] (Supplemental Appendix 3).

Study sample and recruitment

Eligible participants were university students aged 18–34 years; owning an iPhone (model 7 and above) with Internet access; and able to speak, read, and write in English. As an incentive for participation in the study, individuals entered in a draw to win a Fitbit device (i.e. Fitbit Flex 2 or Fitbit Aria scale) at the end of the study. Given that our main aim is to evaluate the feasibility of the be.well app and its unique personalization approach (and not to test efficacy/effectiveness), we followed published heuristics[40,41] for feasibility trials, which indicate that:

1. While a sample size justification is important, a formal calculation may not be appropriate;

2. It is appropriate for sample size of feasibility studies to be based on practical considerations such as recruitment and budgetary limitations.

A sample size of 20 was pragmatically chosen to enable pilot testing, based on the following justifications:

1. The team's practical considerations regarding recruitment and budget;
2. Similar approach taken in other feasibility studies of mobile interventions;[42–44]
3. Our previous experience in mixed-methods research-where a sample size of 20 allowed us to get a diversity in perspectives and experiences, especially regarding the acceptability of the intervention (an important aspect in feasibility)."

Students from Macquarie University (Sydney, Australia) were recruited using convenience sampling methods, via social media and university newsletters from May to June 2020. People interested in participating were redirected to a Qualtrics survey to assess their eligibility criteria. If eligible, people were subsequently invited to attend a pre-intervention study session via Zoom.

Context

During the data collection period (May to July 2020), the COVID-19 pandemic had led to restrictions imposed by the Australian and New South Wales state Government. Specifically, all organized and social sports were suspended, gyms and recreation facilities were temporarily closed from mid-March to early July; and exercise was one of the essential reasons that allowed people to leave their home.[45]

Study procedures

At the pre-intervention study session via Zoom, participants provided written informed consent for participation in the study and filled in a questionnaire about their demographic information and smartphone usage (Supplemental Appendix 4). Subsequently, they participated in an interview (Supplemental Appendix 5) about their perspectives on the role of personalization in physical activity promotion, and their use of mobile apps for physical activity. Finally, participants were guided to download the be.well app on their phones. Participants engaged in a think-aloud session where they were asked to perform some tasks (e.g. set a goal, post a status) in the app and voice their opinion aloud. A list of the think-aloud tasks is included in Supplemental Appendix 6.

Participants used the mobile app for 2 months. The app was available only to the participants and the lead researcher during this time (i.e. not available for public download). After a 2-month study period, participants were invited to attend a post-intervention session via Zoom in which they completed the mHealth App Usability Questionnaire (MAUQ)[46] (Supplemental Appendix 7) and an interview sharing their experience with the app (Supplemental Appendix 5). Their weight and height were collected via self-report to calculate body mass index (BMI, kg/m^2). Each pre-intervention and post-intervention study session took around 45 minutes to an hour.

Intervention

The intervention was a physical activity mobile app (be.well). The app included behavior change techniques identified as effective in previous systematic reviews,[16,17,47–50] and a personalized feature that incorporated users' preferences. The app was designed by the research team and compatible with the iOS system.

The novel feature of the app was the personalized activity suggestion, which regularly took users' preferences into account in its personalization approach. At the end of each week, if the users did not achieve their activity goal, the app prompted users to reflect upon their personal barriers to physical activity (Figure 1(a)). Based on the barriers selected, the app automatically showed three suggestions from a pre-developed list (Supplemental Appendix 8). The list was informed by evidence-based resources from public health agencies[51–56] and reviewed by a clinician and co-authors (Supplemental Appendix 8). The app incorporated users' preferences by allowing them to choose the suggestion that suited them best (Figure 1(b)). As other studies have collected users' preferences at baseline,[26] the novelty of our personalization approach is that users' preferences were incorporated weekly, to take into account users' changing needs and circumstances.

Besides the personalized activity suggestion, the be.well app also included goal setting, self-monitoring, social support, social comparison, and rewards (Figure 1(c) to (f)), because these behavior change techniques were shown to be effective in promoting behavior change.[16,17,47–50] Specifically, participants could set their activity goal, in either number of step count or distance walked/ran. The app incorporated some gamification features by giving users badges when they achieved their activity goal. Users could also self-monitor their step count, weight, and BMI via numerical and graphical display. The step counts displayed were collected by the iPhone accelerometer and gathered via the HealthKit iPhone platform, while height and weight were entered by participants. Additionally, to facilitate the behavior change techniques of social support and social comparison, the be.well app also included a social networking component where participants could post, like, comment, find and add friends, and message other users. Before the study commenced, the be.well app underwent beta testing within the research

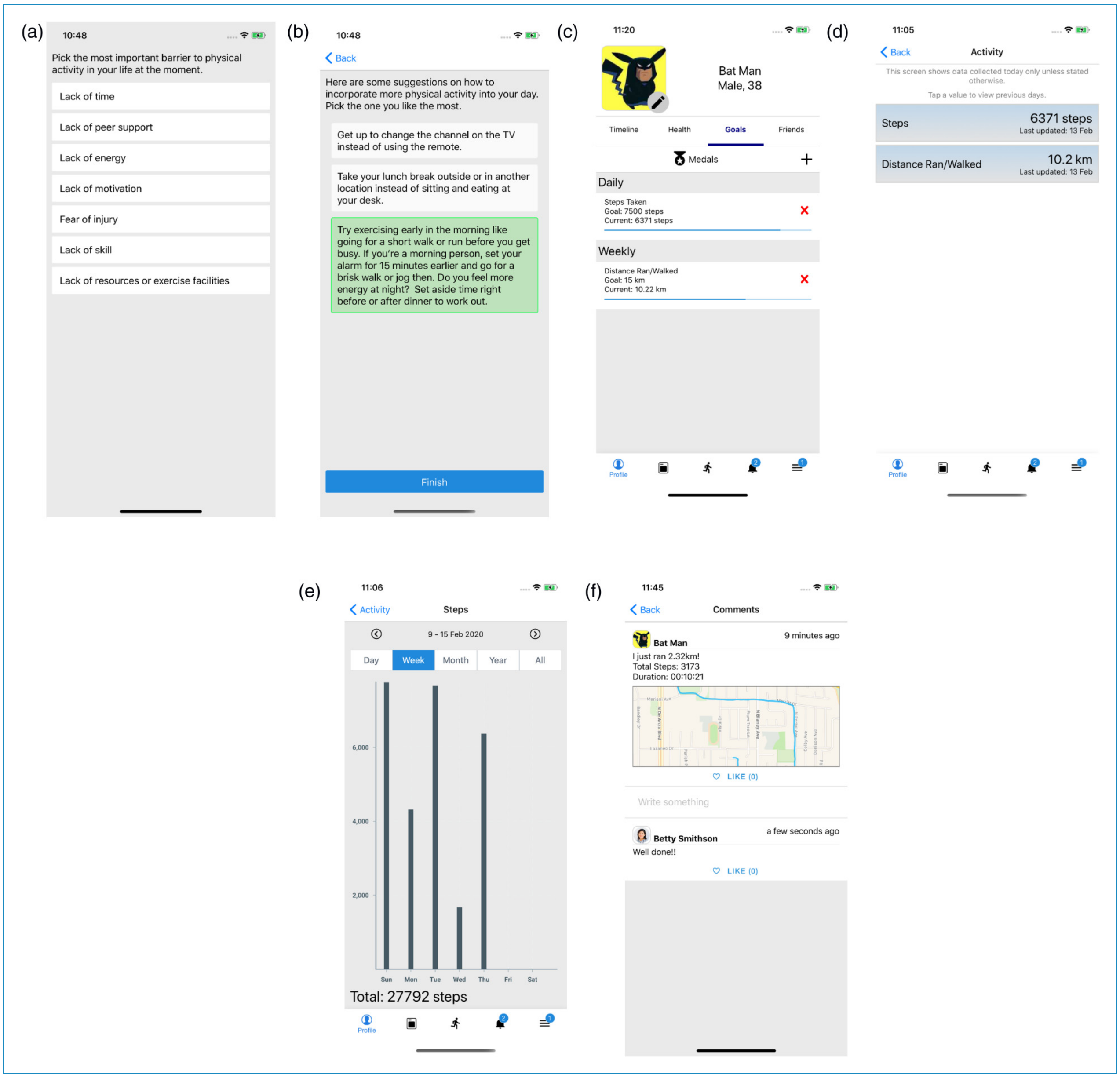

Figure 1. (a) Select barriers to physical activity, (b) pick activity suggestion, (c) goal setting, discrepancy between current behavior and goal, medals, (d) self-monitoring (numerical display), (e) self-monitoring (graphical display), (f) social features.

center with seven users to identify and correct technical problems.

Quantitative data collection and analysis

Usability and engagement metrics. The usability of the be.well app was assessed by the mHealth App Usability Questionnaire (MAUQ)[46] completed at the post-intervention session (Supplemental Appendix 7). The MAUQ is a validated questionnaire comprising 18 statements that seek users' opinions on ease of use, interface and satisfaction, and usefulness of the mobile health app. Participants were asked to rank the statements on a 7-point Likert scale from strongly disagree (scored as 1) to strongly agree (scored as 7). The app's usability was determined by calculating the total score, as well as the average of the responses to all statements. A higher score indicates a higher usability of the app.[46]

Regarding engagement with the app, we report the median daily engagement time. Daily engagement time was defined as the average daily time that the users used the app in the device foreground. We also reported the number of people that used the app in the last month and the last week of the study.

Daily step count. The changes in physical activity were assessed by comparing daily step count between baseline and 2 months, which was measured using the iPhone accelerometer and captured via Apple's HealthKit. Baseline daily step count was considered the median daily step count in the 30 days prior to the be.well app installation (month 0). Specifically, at the pre-intervention session, once participants gave consent and installed the be.well app, the app automatically accessed Apple's HealthKit to capture daily step count in the 30 days prior, which was used to establish baseline. Daily step count at 2 months was the median daily step count for the last 30 days of the intervention.

Statistical analysis. Participants' demographic characteristics and usability score were analyzed descriptively using means, standard deviations (SD) and frequency counts. The step data followed a non-normal distribution, and thus, Wilcoxon signed rank test was used to compare median daily step count between: (1) baseline period (month 0) and at the end of the study (month 2), (2) baseline period (month 0) and the 1st month intervention period (month 1). It is known that users might occasionally forget to carry their phones, leading to very low step count on some days.[57] Including days with low step count could underestimate the levels of physical activity and bias the results. Thus, we performed two analyses: one with all the step counts and a sensitivity analysis excluding days where people had less than 100 steps.[42] To explore the effects of the personalized activity suggestion feature on step count, we analyzed changes in daily step count between baseline (month 0) and at the end of the intervention period (month 2) amongst users who viewed the activity suggestions.

Exploratory subgroup analysis was conducted to investigate the changes in step count for specific subsets of the participants, based on their BMI, and the app usability score they provided. Specifically, we examined the following groups: people who were overweight and obese (BMI ≥ 25 kg/m^2), people who had normal weight (BMI < 25 kg/m^2), people who had the usability score above the group mean, and those with the usability score below the group mean.

Data were analyzed using R version 4.0.3;[58–60] figures were created in R and Excel. The significance level for all statistics tests was set at $p < 0.05$, two-tailed, and 95% confidence intervals (CIs) were calculated where applicable.

Qualitative data collection and analysis

Intervention acceptability was assessed via individual interviews. Individual interviews were conducted by a trained researcher at both the pre- and post-intervention sessions via Zoom. Prior to study commencement, an interview guide was developed, pilot-tested, and revised to improve the flow and wording (Supplemental Appendix 5). At the pre-intervention session, participants attended the interviews where they talked about their habits of using technologies for physical activity, and their perception on personalized features of technologies. The content of the pre-intervention interviews was summarized and used as prompts for discussion in the post-intervention sessions. At the post-intervention interviews, participants shared their experience using the be.well app and its different features. App usage data and usability data (from the MAUQ responses) were used as prompts to discuss participants' engagement with the app and what features they liked/disliked. A time-series graph of their step count data was also shown to participants to prompt discussion on why they might or might have not engaged with physical activity. Field notes were taken throughout the interviews. Data saturation was reached, that is, no new content emerged after three consecutive interviews by the time we interviewed 18 participants.

The interviews were audio-recorded and transcribed verbatim. The transcripts were analyzed in NVivo 12,[61] using thematic analysis techniques[62] by two trained researchers. First, the transcripts were open coded to identify all important aspects related to the research questions. Through constant comparison, codes and concepts were clustered together to form subthemes, and further abstracted to major themes, which were then reviewed and refined in light of existing literature with a third researcher. Quantitative and qualitative results were integrated through the embedding of data. Integration is presented throughout the *Discussion* section.

Results

Sample characteristics

A total of 23 participants (mean age 21.9 ± 2.6 years, 71.4% women) were enrolled in the study. Out of the 23 enrolled participants, 20 participants (86.7%) returned for the post-intervention sessions (i.e. study completers). Five participants' step data was excluded from the analysis of step count due to a high rate of missing or absent data (Supplemental Appendix 9). In total, the step count data included 18 participants. Participants reported that on average, they used their iPhone approximately 4 hours daily and most participants (17/21, 80.9%) had used other health apps in the past. The most popular health app used was Apple Health (7 out of 17 (41%)). The average BMI was 25.7 kg/m^2 (SD 4.6).

Quantitative findings

App usability and engagement. The mean MAUQ usability score was 5.6 out of 7 (SD 0.8), indicating high usability of the be.well app. In particular, ease of use of the app was rated highly (average score of over 6 out of 7). Participants also gave a 4.9 out of 7 (i.e. somewhat agree) for the two statements "The app helped me manage my health effectively," and "This app has all the functions and capabilities I expected it to have." The lowest scores were 4.5/7 (i.e. neither agree or disagree) for the statement "I could use the app even when the Internet connection was poor or not available." In the interviews, participants mentioned that the app interface looked simplistic, and more color could improve the look. Figure 2 shows participants' response to the MAUQ.

The median daily engagement time was 2 minutes. Engagement with the app declined over time. Out of 23 participants, 18 participants still used the app in the last month of the study; only 10 used the app in the last week. The MAUQ response showed that 17 participants (85%) agreed that they would use the app again.

Changes in daily step count. Daily step count increased after two months of the intervention (median difference = 1953 steps/day, p-value <.001, 95% CI 782 to 3112); there was no significant change in daily step after one month of the intervention (median difference = 697 steps/day, p-value = .07, 95% CI −58 to 1845). Figure 3 shows individual participants' step count data over time. A sensitivity analysis excluding days with less than 100 steps also showed similar results (Supplemental Appendix 10).

To explore the effects of the personalized activity suggestion feature, we examined the subset of users who viewed this feature (i.e. 16 users). The 16 users who viewed the activity suggestion feature increased their step count at the end of the 2-month intervention period (median difference = 1858 steps/day, p-value = .003, 95% CI 444 to 3278).

Subgroup analysis found that after the 2-month intervention period, people who were overweight and obese (n = 10) increased their step count significantly (median difference = 2068 steps/day, p-value = .0097, 95% CI 554 to 3606; no significant change in daily step count for the normal BMI group (n = 7); difference between BMI groups non-significant). Additionally, people who rated the MAUQ usability score above the group mean (n = 10) increased their step count (median difference = 2219 steps/day, p-value = .004, 95% CI 566 to 4518; no change in pre–post daily step count for the subgroup who rated the MAUQ usability score below group average (n = 7). Figure 4 shows the results of these subgroup analyses, indicating the pre–post differences in daily step counts within groups and respective p-values. Per reviewer's suggestion, we ran post-hoc correlation test to explore potential relationships between average daily phone usage reported at pre-intervention sessions and (1) the MAUQ score and (2) step count, and did not find any statistically significant correlation (Supplemental Appendix 11).

Qualitative findings

We conducted 20 individual interviews (15–45 minutes in length). The central themes were: (1) users taking control

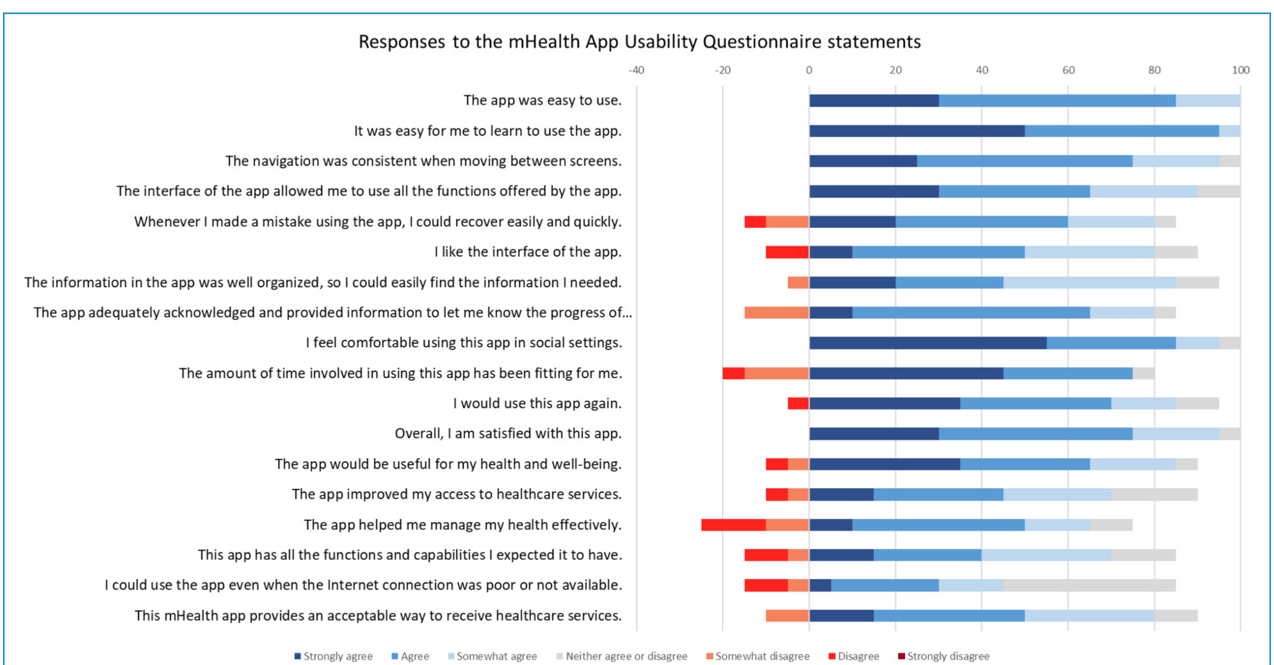

Figure 2. Responses to the mhealth App Usability Questionnaire statements.

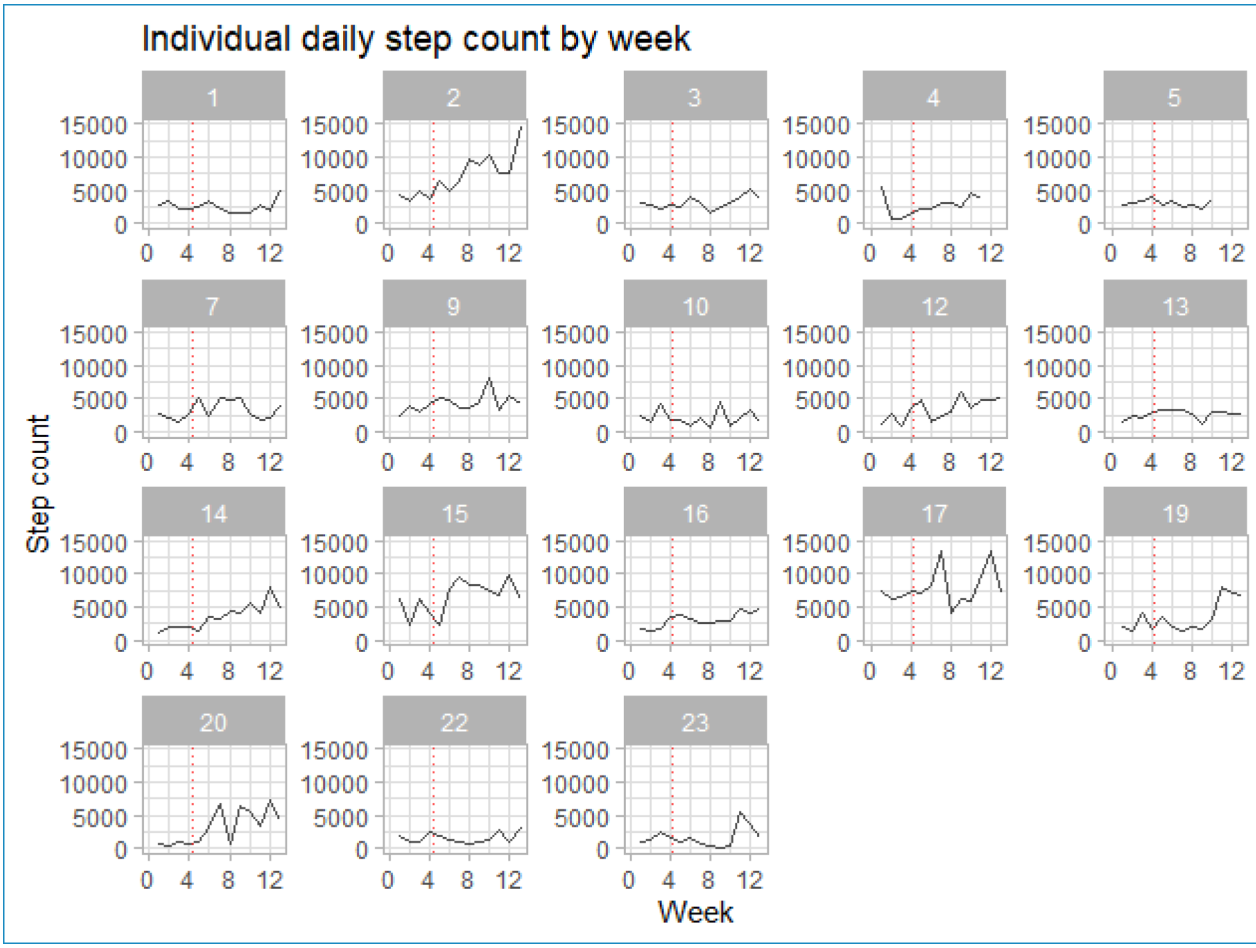

Figure 3. Individual participants' weekly average of daily step count. Red line represents the end of the baseline period.

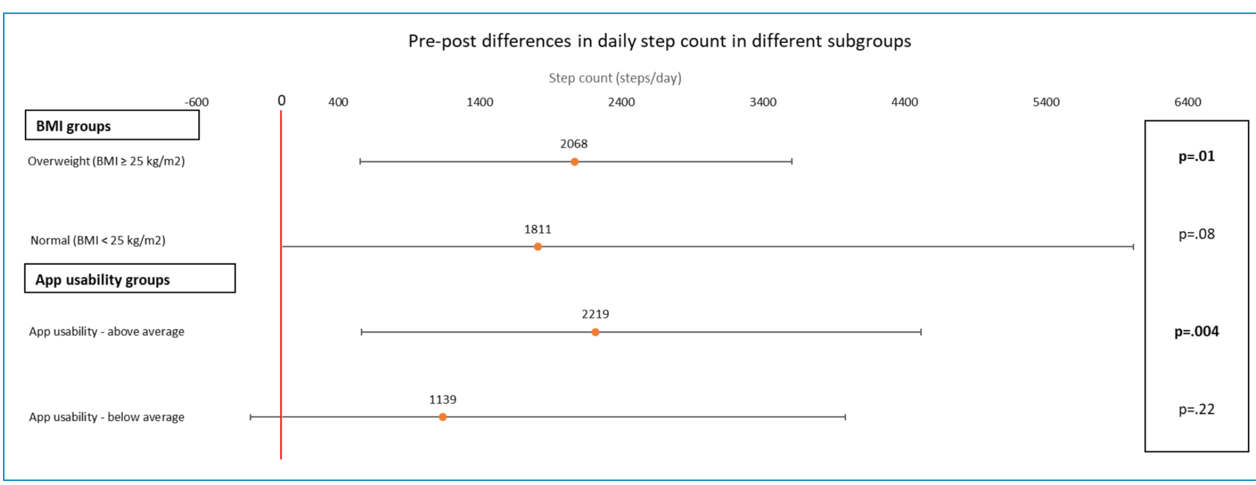

Figure 4. Pre-post differences in daily step count in four subgroups: (1) people who were overweight and obese, (2) people who had normal BMI, people who rated the MAUQ usability score, (3) above average, and (4) below average. Subgroup analyses found a significant change in daily step count for group 1 (overweight and obese), and group 3 (app usability score above average).

of action planning, (2) varying preferences for the degree of personalization, and (3) personalization of social comparison. Participants felt that the personalized activity suggestions empowered them by allowing them to choose what suggestions to follow. Participants expressed different preferences regarding the degree of personalization, with some also expressing preferences for less personalized features due to privacy concerns. Participants highlighted the need for social comparison to be personalized based on similarity (e.g. comparison with similar body types) and preferences for upward or downward comparison. The following discusses these themes in more detail with illustrative quotes (Table 1).

Users taking control of action planning. Most participants mentioned that they liked the personalized activity suggestion feature because it allowed them to exercise their control and autonomy by picking personal barriers and relevant suggestions (quotes 1-2). Some participants mentioned that the personalized feature prompted them to reflect upon their barriers to physical activity, and provided actionable, easy to implement activity suggestions (quotes 3-4). One participant compared the feature to having a personal coach that is empowering one to learn (quote 5).

Varying preferences for the degree of personalization. Participants expressed varying preferences regarding the degree of personalization, ranging from general features to more personalized features. On one hand, some participants mentioned that the app should leverage more personal data such as location or habits to deliver more personalized suggestions (quote 6). Some were happy to share personal data in exchange for receiving highly personalized features, as long as the app was transparent about what data were collected and how they would be used (quote 7). Some people also expressed that they would like to receive more personalization, such as the ability to input their own barriers (quote 8), or to have personalized timing of receiving the suggestions (quote 9). On the other hand, some participants would prefer less personalized features, as they valued their privacy and did not want to share personal data (quotes 10-12). In the middle of this spectrum, some participants preferred a balance between sharing personal data and personalization, citing that they liked the personalized activity suggestion because it did not collect too much personal data while still giving them personally relevant advice (quote 13).

Personalization of socials comparison. Participants highlighted the importance for social comparison to be personalized based on similarity and different preferences for upward or downward comparison (i.e. comparison with more or less active people). Most participants valued similarity (i.e. "following" people who have similar goals or body types) (quotes 14-17). However, there were contrasting preferences regarding upward or downward comparison, which highlighted the need for personalization based on preferences. Preferences varied between people, with some participants prefer comparing with more active people (quotes 18-19), while others found that demotivating (quote 20). Preferences also varied within the same person, as some participants mentioned wanting to have both upward and downward comparison (quote 21).

Discussion

Main findings

This study demonstrated the feasibility and acceptability of a physical activity mobile app that regularly includes users' preferences in its personalization approach. The app usability score was high, and most participants found the personalized activity suggestion feature to be actionable and promote user autonomy. Preliminary data suggests positive effects on daily step count; the subgroup of participants who were overweight and obese, and the subgroup of people who viewed the personalized feature experienced an increase in daily step count. Qualitative data reveal that some users might be reluctant to use personalized features if that required them to provide a large amount of personal data. Participants also highlighted the need for social comparison to be personalized based on their preferences.

The potential of a personalized mobile app for physical activity

Our 2-month study found that users increased their step count, which adds to the current evidence on the promising effects of personalized mobile apps on physical activity.[17,26] Existing reviews have suggested a positive, but small effects of personalization on physical activity.[26,63–65] It is worth noting that most studies included in those reviews had short duration and small sample size, and some did not utilize a lot of users' information and thus, were only personalized to a small extent. Little is known about the long-term impact of personalization in mobile apps on sustaining physical activity behavior. Fully powered trials with longer follow up are needed to ascertain the effects of personalization on physical activity. Given the dynamic and idiosyncratic nature of physical activity, dynamic personalization features could better accommodate for more changes in users' daily life and context, and help people meet recommended levels of physical activity.[32] A venue for future research might be to examine *how much* personalization is needed to motivate changes in physical activity, and whether highly personalized, dynamic interventions might lead to larger changes.

The personalization and privacy paradox

Qualitative data suggests that some people might enjoy personalized features but are reluctant to share personal information needed to enable the delivery of such features. This phenomenon is known as the personalization-privacy paradox[66] where privacy concerns might hinder users' adoption of personalized technologies. Previous research

Table 1. Illustrative quotations for qualitative findings.

Users taking control of action planning

1. "I liked [that] you could pick which one appealed to you the most. It gave you a few to pick from so you can assess 'what do I think is personally manageable to me', 'which one do I think would work best for me?'" (F, 26)
2. "I could select the options that were best for me. It was up to me to decide what was holding me back and what I think the best way for myself to improve would be." (F, 18)
3. "I like to reflect and identify issues. [The feature] would make me think 'What's the reason? Why didn't I walk and hit this goal.' I like that it forces me to reflect on what happened." (G, 21)
4. "They were just little changes which I quite liked. A lot of the times if you're having motivation problems, a lot of advice is 'You have to completely change your routine. Do these massive changes', which is unattainable. Whereas little changes are good." (F, 26)
5. "In Fitbit (that was the app I used before), it just says you didn't reach a target, and you're like 'I know'. Having that personalized feature is almost like a coach being 'come on, step up your game', which is nice. It's helping you learn." (F, 19)

Varying preferences for the degree of personalization

6. "It might be interesting if the app can pick up a location or other habits to make more personalized suggestions." (F, 26)
7. "There's this whole conversation about data being used by companies to understand you as a person better than anyone else would and then manipulate you to buy things. But if it's for a fitness app, then [...] that's one good use of it. For example, they give me KFC ads on YouTube at certain times of the day and I have to just look away. But if it could be used in a way that advertises physical activity, then I think that's a really good idea. If that knowledge can be used to make people healthier then why not? And I think if a person consents to [the collection of personal data] then that's fine, so long as it's super transparent that they're going to use what data and how." (F, 23)
8. "I thought what might have been helpful is if there was an option where you can type your own response, because I wasn't always sure what to pick in the reasons why." (F, 26)
9. "When you set it up, you can choose the preferred time when you'd receive the [prompt]." (M, 24)
10. "I think [having more personalized features] is not necessary, because I just [want to share] general information about me. If [the app] is too specific, sometimes we feel like they try to control our life. Some information in our life – I feel like it's [...] private. For me, just general [feature] is enough." (F, 23)
11. "I tend to be a more private person, so [sharing personal data] is a bigger concern to me. Even with the generalized feature, I was pretty happy with what I got. In some of the other fitness apps I use, I usually keep it pretty general. For example, I go in [the app] for a purpose, like just to record my workout." (M, 20)
12. "I have an issue with [...] having an app know a lot of stuffs about me. It's my personal preference, not to disclose a lot of things about me online or on the digital platform." (G, 21)
13. "I think [the personalized activity suggestion]'s at the perfect level because it doesn't intrude too much on your [...] personal life but at the same time it forces you to be honest with yourself and gives you good advice." (M, 22)

Personalization of socials comparison

<u>Similarity</u>

14. "I feel like even if you don't know people, you [might be] following each other because you have something in common. That can make it more personalized. I'd be inclined to actually care if I know that they are doing similar things to me." (F, 18)
15. "If [the app] can separate people into different groups like people that have similar goals, or at a similar level to you, so you can track your progress alongside and be inspired by them, or get help with encouragement." (F, 27)
16. "On [fitness apps], I find myself following a lot of strangers who have similar interests [to me] but they have also reached goals that I want to achieve." (F, 23)
17. "If people are on a similar level [with me] and they are progressing and it's like a clear, noticeable change or progression, that makes [fitness goals] seem more attainable for myself. Like "oh if they are the same as me and they are now able to do this like, surely I can as well" and that might just push me a little bit harder to try and keep up [...] Whereas if it's someone that's already really fit, I'm just like "oh, that's just unattainable right now," like that's so far ... out of my league." (F, 27)

<u>Different preferences for upward or downward comparison</u>

18. "When I saw people doing 25 km run a day, I hit "follow." I want to see [them] more often to hold me accountable. That would be motivation. You can see someone else doing 25km run a day but you're doing 5 km, [it makes me think] I might do 7 km tomorrow and up my game.") (F, 19)
19. "[I saw] this person who was a long-distance runner and did crazy run almost every day. I think that's super impressive but also slightly intimidating. I did notice that I might have been intimidated by that and pushed away. But I then realized I was being silly, and I should just do my own thing and let it motivate me instead. People who are more fit than me might motivate me more because they tend to be more impressive. [...]If someone posts "I only did an hour walk today even though I wanted to do two hours. It's ok because I was feeling tired from the day before"[...], it's too relatable and allows me to fall into those traps of [...] not doing as much as I can." (F, 23)
20. "Maybe if you're sharing with someone who's [at] a much higher fitness level than you, seeing them do like 28 kilometers a day and you're doing like 2 kilometers, I suppose that can be demotivating." (M, 21)
21. "[I want to follow] people who are more fit than me, because I can look at what they're doing and be 'I want to aspire to that'. But [I also want to follow] (and this is probably selfish) people that were less fit than me so that I can feel a bit better about myself." (F, 18)

Note: The bracket provides gender and age. F: female, M: male, G: genderqueer.

has shown that health apps can exhibit significant privacy issues,[67–69] which could leave users vulnerable to commercial exploitations.[70] To ensure that users feel comfortable and safe to benefit from personalization, better privacy regulation and transparent disclosure of data sharing processes (e.g. such as those required by the General Data Protection Regulation) should be addressed by policymakers.

The preferences of social comparisons for physical activity

In line with prior research,[71] our study found varying preferences for social comparison between people and even within the same person over the course of behavior change. This highlights the need for personalization based on users' preferences, as both upward and downward comparison can have positive effects: upward comparison helps boost motivation, while downward comparisons increases self-confidence.[72] Perhaps physical activity apps can leverage the principles of existing social media apps (e.g. Facebook or Instagram) to accommodate for different preferences, by detecting and showing content from whom users tend to follow and interact with. Altogether, this suggests that personalization in response to personal and environmental changes could help maximize the positive impact of social comparison.

Implications

Our findings add support to the growing evidence that mobile apps can lead to short-term increases in step count.[17,18,24] A personalization approach that regularly includes users' preferences appears to be promising, with qualitative evidence showing that users liked exercising their autonomy by choosing what app suggestions to follow. Future research is needed to understand how personalization might influence motivation, autonomy, and the causal behavioral mechanisms that drive behavior change.[73] Given the pre–post nature of our experiment, future research with longer follow up and comparison group is warranted to confirm the results of this pilot trial. To better examine the effects of personalized features, study designs such as N-of-1[74] or micro-randomized controlled trials[75] might be suitable, as they can evaluate different intervention components, intra-individual differences, and time-varying effects.

Our study contributes towards understanding how users' preferences can be incorporated in personalized mobile apps for physical activity promotion. Future studies using qualitative, or design thinking methods could explore how to incorporate users' preferences to shape the personalization algorithms from data collection to the delivery of personalization. Specifically, research should explore the role of meta-personalization: how to personalize options within a mobile app based on the extent users want to use such features, the amount of data they were willing to share in exchange for more personalization, and the amount of control they want to have over the algorithms.

It is worth noting that our personalization algorithm uses a rule-based approach. An interesting venue for future research is to examine whether data-driven interventions that use machine learning algorithms might offer more personalization and potentially lead to better health outcomes. Current machine learning algorithms can process a large amount of data to reveal behavior patterns and deliver personalization;[76–78] however, they require the collection and storage of personal data, such as users' habit, behaviors, location, or social interaction. Given our findings of privacy concerns, research is needed to understand the acceptability of personalization, and particularly, to what extent users want to share their personal data in exchange for more personalization.

Strengths and limitations

The strengths of this study include the mixed-methods design which allowed us to examine both the quantitative impact of the app (including usability, engagement metrics, and step data), and qualitative users' perspectives of the app. Step count was objectively measured using the smartphone accelerometer, instead of self-reported data. Baseline measurements were established retrospectively, meaning that participants were blinded during the baseline period.

It is important to interpret the findings of this study within its context and limitations. Our study was conducted during the pandemic (i.e. May to July 2020) with public health restrictions, which might have impacted people's normal activity and exercise patterns. For example, a worldwide dataset showed a decrease in mean daily step count during the pandemic.[79] A limitation of this study is a short intervention period (2 months), and the nature of one-arm, pre–post experiment, which means that we cannot draw conclusions regarding causation. Our findings might also be affected by the Hawthorne effect where participants might have modified their behaviors because they participated in an experimental study. Our sample was limited to university students in early adulthood, who were likely digitally savvy. This sample might have found using our app for physical activity easier, given that most had used health apps in the past. They might have also expected a more sophisticated user interface, as suggested in the MAUQ response and interviews. Future research testing on other population groups, especially on those less digitally savvy, is warranted. Participants' weight and height were only collected at post-intervention. Physical activity was measured via step count and did not include other types of activities, nor intensity of the activities. Moreover, step count data were measured by the phone accelerometer, and could have underestimated true step count levels, as it is known that users might occasionally forget to carry their phones.[57] We tried to mitigate this by performing a sensitivity analysis excluding days where people had less than 100 steps.[42] Our personalized feature was derived using rule-based methods. Our intervention was multi-component, and our pre–post study design was not able to isolate the effects of personalization. We attempted to examine the impact of the personalization feature by conducting a subgroup analysis of users who were exposed to it. Future research is encouraged to adopt suitable study designs such as N-of-1 or micro-randomized control trials to identify the effects of different intervention components.

Conclusion

A mobile app that regularly includes users' preferences to personalize physical activity advice is feasible and acceptable, with preliminary support for its positive effects on daily step count. Future research with suitable study designs and longer follow up is warranted to better examine the effects of personalization.

Acknowledgements: We would like to thank Mr Jason Dalmazzo for his assistance in the be.well app development. We thank Mr Vitaliy Kim, Dr Dana Rezazadegan, Ms Kim Phuong Dao, Ms Agustina Briatore, Ms Antoinette Pavithra, Ms Saba Akbar, and Dr David Fraile Navarro for their help in the initial app testing. We thank Ms Nesrine H'mada for her assistance in qualitative data analysis during her Honours program. Our gratitude goes to the students at Macquarie University's Professional and Community Engagement (PACE) program for their assistance in data transcription and preliminary analysis, including Mr Alexander Southern, Ms Sally Chen, Mr Michael Alam, Mr Joshua Irawan, Ms Yoonah Kim, Mr Huygo Jo, Ms Heather Varcoe, Mr Mark Knappe, and Mr Anthony Sharobim.

Conflict of interest: The authors have no conflicts of interest to declare.

Contributorship: Study conceptualization: HLT, LL, JCQ. Study design: HLT, LL, JCQ, ABK, KI. Participant recruitment & data collection: HLT. Data analysis: HLT, LL, JCQ. Writing first draft: HLT. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Ethical approval: Ethics approval was granted by the Human Research Ethics Committee for Medical Sciences of Macquarie University (reference number: 52020638214729).

Funding: The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: HLT was supported by the International Macquarie University Research Excellence Scholarship (iMQRES) (Macquarie University funded Scholarship – No. 2018148) and the Australian Government Research Training Program Scholarship. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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Supplemental material: Supplemental material for this article is available online.

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