Effectiveness of a Just-In-Time Adaptive App to Increase Daily Steps: An RCT

Vos, A.L.; de Bruijn, G.J.; Klein, M.C.A.; Boerman, S.C.; Stuber, J.M.; Smit, E.G.

DOI
10.1016/j.amepre.2024.09.010

Publication date
2025

Document Version
Final published version

Published in
American Journal of Preventive Medicine

American Journal of
Preventive Medicine

RESEARCH ARTICLE

Effectiveness of a Just-In-Time Adaptive App to Increase Daily Steps: An RCT

Anne L. Vos, PhD,[1] Gert-Jan de Bruijn, PhD,[2] Michel C.A. Klein, PhD,[3] Sophie C. Boerman, PhD,[4] Josine M. Stuber, PhD,[5] Edith G. Smit, PhD[1]

Introduction: Addressing the public health problem of physical inactivity, this study evaluates SNapp, a just-in-time adaptive app intervention to promote walking through dynamically tailored coaching content. It assesses SNapp's impact on daily steps and how users' perceptions regarding ease of use and usefulness moderated its effectiveness.

Methods: SNapp was evaluated in an RCT from February 2021 to May 2022.This trial was preregistered in the Dutch Trial Register (NL7064). Analyses were conducted in November 2022. A total of 176 adults (76% female, mean age of 56 years) were randomized to a control group receiving a step counter app (n=89) or an intervention group receiving the app plus coaching content (n=87). SNapp's coaching content encompasses individually tailored feedback on step counts and advice to engage in more walking, taking preferences regarding behavior change techniques into account. Additionally, SNapp provides contextualized content calling attention to suitable walking locations in the user's environment. The primary outcome was daily step count as recorded by the step counter app. User perceptions regarding ease of use and usefulness were assessed via survey at 3-month follow-up.

Results: Mixed models indicated that the intervention did not significantly impact step counts on average over time (B= −202.30, 95% CI= −889.7, 485.1), with the coefficient indicating that the intervention group walked fewer steps per day on average, though this difference was not statistically significant. Perceived ease of use did not moderate the intervention effect ($B_{\text{group} \times \text{perceived ease of use}}$=38.60, 90% CI= −276.5, 353.7). Perceived usefulness significantly moderated the intervention effect ($B_{\text{group} \times \text{perceived usefulness}}$=344.38, 90% CI=40.4, 648.3).

Conclusions: SNapp increased steps only in users who deemed the app useful, underscoring the importance of user perceptions in app-based interventions.

Am J Prev Med 2025;68(1):154−163.

INTRODUCTION

Physical inactivity is a global public health problem, contributing to the prevalence of noncommunicable diseases, including diabetes, cancer, and cardiovascular disease.[1−4] This issue is pressing in areas of low socioeconomic position (SEP), as residence in socioeconomically disadvantaged neighborhoods has been associated with lower physical activity (PA) levels.[5−7] Moreover, health interventions often fail to reach all population segments, which can reinforce socioeconomic health disparities.[8,9] Therefore, it is vital to find effective

From the [1]Amsterdam School of Communication Research, University of Amsterdam, Amsterdam, The Netherlands; [2]Department of Communication Studies, University of Antwerp, Antwerp, Belgium; [3]Social Artificial Intelligence Group, Department of Computer Science, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands; [4]Strategic Communication Group, Wageningen University & Research, Wageningen, The Netherlands; and [5]Epidemiology and Data Science, Amsterdam University Medical Centers, Location Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

Address correspondence to: Anne L. Vos, PhD, Amsterdam School of Communication Research (ASCoR), University of Amsterdam, Nieuwe Achtergracht 166, 1018 WV Amsterdam, The Netherlands. E-mail: a.l.vos@uva.nl.

0749-3797/$36.00
https://doi.org/10.1016/j.amepre.2024.09.010

approaches to increase population-level PA across socioeconomic groups.

Increasing walking is considered a viable solution to physical inactivity for individuals of various ages and population segments. Generally, walking is a simple, safe, and free activity that can be performed anywhere and anytime.[10] Nonetheless, this may not apply to everyone, including those with health issues, living in unsafe areas, or facing time and financial barriers. Walking has been shown to provide health benefits, including the reduction of risks associated with chronic diseases.[11] Apps have attracted attention as promising tools for delivering walking interventions on a large scale.[12] Built-in sensor functionalities allow smartphones to monitor step counts unobtrusively. Apps can use this information to provide real-time feedback on walking behavior to many users at a low cost.[13] These benefits make apps attractive for providing interventions to increase population-level PA.[14]

Apps allow the design of interventions that offer the right support at the right time. Such interventions are referred to as just-in-time adaptive interventions (JITAIs[15−17]). The distinction between JITAIs and standard interventions is that they account for an individual's changing states of need and opportunity for behavior change to provide appropriate support when needed. To do this, JITAIs often rely on data from smartphone sensors. For example, an app-based JITAI can use smartphone sensors to automatically provide support at moments that facilitate opportunities to engage in PA based on the user's location, such as a nearby park. Although a recent meta-analysis has demonstrated the short-term efficacy of JITAIs in various domains,[18] research into JITAIs for PA promotion is still in its early stages, and more evidence on their effectiveness is needed.[15,16]

In this context, SNapp was developed, an app-based JITAI aiming to stimulate walking. SNapp was designed to engage users by leveraging smartphone capabilities, such as location tracking, to detect and encourage opportunities for walking in real-time.[19] SNapp was implemented in a 12-month RCT in 12 municipalities in the Netherlands to evaluate its effectiveness.[20,21] Smartphone users aged 30−80 years were recruited from socially disadvantaged areas to promote increased inclusivity of all population segments within the trial. This study's primary objective is to evaluate SNapp's effectiveness in increasing step counts.

Its second objective is to investigate the moderating role of user perceptions on the intervention's effect. This study, informed by the Technology Acceptance Model,[22] examines the influence of perceived ease of use—the degree to which app use is seen as free of effort—and perceived usefulness—the extent to which app use is seen as beneficial. Prior research has demonstrated that these perceptions are associated with increased app use and higher intentions to continue use.[23−25] This study hypothesizes that more positive perceptions of ease of use and usefulness will enhance SNapp's impact on daily steps, marking a novel approach in examining the effect of user perceptions on JITAIs' health behavior effects in a longitudinal real-life setting.

METHODS

SNapp was part of the Supreme Nudge trial, which aimed to improve lifestyle behaviors through a supermarket intervention and app-based PA coaching. The supermarket intervention involved implementing nudging and pricing strategies, with the goal of improving diet quality and purchasing patterns among regular shoppers. Details of the Supreme Nudge trial have been described elsewhere.[20,21,26,27] The study protocol was approved by the Medical Ethics Review Committee of the VU University Medical Center (2019.334). The study was preregistered in the Dutch Trial Register (NL7064).

Conducted across 12 municipalities in the Netherlands, the Supreme Nudge trial initially enrolled participants from 8 municipalities in winter 2021 and expanded to 4 additional municipalities in autumn 2021 due to low enrollment rates. The trial lasted 12 months for the initial municipalities and 6 months for the subsequent ones, constrained by funding limits. The trial had a randomized controlled design consisting of a control arm (n=6 municipalities) and an intervention arm (n=6 municipalities) receiving the supermarket intervention. Additionally, SNapp was randomized at the participant level. Participants were randomized to a control group receiving a step counter app or an intervention group receiving a step counter app plus coaching content (further explained below). A research assistant carried out randomization using Castor Electronic Data Capture. A variable block randomization method was employed with blocks of 2, 4, and 6, ensuring equal representation in each group. Participants were informed about their group assignment as it required them to install specific app features.

Study Population

Participant recruitment employed passive (e.g., flyers) and active methods (e.g., on-site recruitment). Details are outlined elsewhere.[28] Participants were informed of a grocery box reward upon study completion. Eligibility criteria included residency in a low SEP neighborhood, as determined by postal code SEP-scores,[29] age between 30 and 80 years, Dutch proficiency, ambulatory status, experience with text messaging, and ownership of a smartphone with a mobile data plan and Android 8, iOS 13, or more recent versions installed. There was no racial or gender bias in the selection of participants.

Individuals willing to participate signed up via website, phone, or mail and were screened for eligibility through an online questionnaire. Eligible candidates received study details and an informed consent form. After obtaining informed consent, participants were randomly assigned to an experimental condition and received an invitation to complete an online baseline questionnaire. Participants also received instructions for installing SNapp and guidelines on using its features. They were informed that the aim of the study was to measure step counts and were asked to keep the app running on their smartphones and to carry their phones on their bodies. Participants authorized their step count and geolocation data to be captured for the study. There was a 7-day baseline period where the app only collected step counts. After this period, the intervention group began receiving coaching content. Follow-up questionnaires were administered at 3, 6, and 12 months. Midway through the study, participants were reminded to keep the app running and to carry their phones on their bodies.

Intervention

The intervention included a step counter app and dynamically tailored coaching content. SNapp's development is detailed elsewhere.[19] The step counter app functioned by continuously quantifying steps using the smartphone's pedometer or accelerometer sensor and was designed to run in the background when the phone was carried on the body. It also periodically checked the participant's location against a database of green spaces suitable for walking (e.g., parks), recording the type of space when within 300 meters, without storing precise coordinates. This privacy-aware app, compatible with Android and iOS, had a user-friendly interface featuring the daily step count. The app's accuracy was validated against standard step counter apps and GT3X ActiGraph accelerometers among a convenience sample of 20 participants, showing acceptable Spearman's correlation coefficients of 0.62 and 0.66, respectively.[28]

The intervention group additionally used Telegram Messenger to receive coaching content. After registering their user ID with the SNapp Telegram account, participants received daily push notifications with coaching messages. These messages were generated by a server-based Python program that utilized databases with user data and a message library, applying logical rules to select messages to send based on relevant conditions (e.g., time of day). Coaching messages were classified into 3 types: feedback on current step counts, contextual prompts when users were near green spaces, and messages reflecting individual behavior change technique preferences (e.g., action planning) identified through the baseline questionnaire. Examples of SNapp's coaching messages are provided elsewhere.[19]

Measures

The primary outcome, daily step count, was recorded by the app and updated hourly in a database over the course of the 12-month intervention period. The collected data were examined to identify unusual values. Based on previous studies,[30−33] days with less than 100 or more than 30,000 steps were considered outliers. Step count values below 100 were removed, and values above 30,000 were truncated. The number of steps taken per day was averaged over a 7-day baseline period to calculate participants' baseline step counts.

Additionally, 2 user perception variables were measured in questionnaires administered at 3, 6, and 12 months. To measure the app's perceived ease of use, participants responded to 3 items on a 7-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (7).[34] An example item was *How the user environment of the walking app works, is easy for me to understand* (Cronbach's α=0.97). As most participants completed the first follow-up questionnaire, these scores were used in the analyses. This decision was further supported by the fact that a repeated measures ANOVA confirmed that there were no significant differences between scores measured at 3, 6, and 12 months (F[2, 140]=0.12, p=0.885). The average score at 3 months was 4.89 (SD=1.81).

Four items were used to assess the app's perceived usefulness.[34] An example item was *The walking app is valuable for me to track progress toward my daily walking goal* (Cronbach's α=0.97). Response options ranged from *strongly disagree* (1) to *strongly agree* (7). In line with previous reasoning, the perceived usefulness scores used in the analyses were also measured 3 months post-baseline. It was confirmed with a repeated measures ANOVA that there were no significant differences between scores measured in the other follow-up questionnaires (F[2, 140]=1.63, p=0.200). The average score at 3 months was 3.31 (SD=1.88).

Statistical Analysis

For the Supreme Nudge trial, a sample of 352 participants was deemed sufficient to detect a significant difference between intervention and control groups with 80% power and a 0.05 significance level, factoring in a 25% dropout rate. The recruitment target was 360 participants, with an expectation to randomize around 300 participants to SNapp's experimental groups. Details of the sample size calculations are reported elsewhere.[20,21]

Statistical analyses were conducted in November 2022 using IBM SPSS Statistics, version 27. Linear mixed models with maximum likelihood estimation and a 2-level structure were applied to assess intervention effects, using the experimental group as the independent variable and daily step count as the outcome variable, with a random intercept at the participant level to account for the hierarchical structure of the data. Residuals were inspected to confirm approximate normal distribution. Models were adjusted for baseline step count to take regression to the mean into account. Smartphone operating system and sensor type were included as covariates in the models, as both were found to be relevant confounders of the main intervention effect. Given no differences between adjusted and unadjusted models, only the adjusted models are reported. Missing data were not imputed due to mixed models' ability to handle these.[35] Medians and interquartile ranges were used to report step counts due to non-normality.

To assess whether the intervention's effect on step counts varied over time, interaction terms between the experimental group and time points were added. Time points were set in 28-day blocks from the start of each participant's intervention, labeled sequentially. This method allowed the comparison of step counts over consistent periods without being affected by the varied trial start dates of participants. Moderation effects of perceived ease of use and perceived usefulness on the intervention's effect were investigated by introducing separate interaction terms between the experimental group and each moderator into the model. Significant interaction was identified by the exclusion of 0 within the 90% CIs, acknowledging the study was not initially powered for detecting subgroup differences.

RESULTS

Participants' flow from randomization to analysis is illustrated in Figure 1. A total of 326 participants were randomized in the study. Of these, 72 were excluded for reasons listed in Figure 1. The remaining 254 participants completed the baseline period. Afterward, 78 participants were lost to follow-up for reasons listed in Figure 1. A total of 176 participants were included in the analyses, of which 87 were part of the intervention group and 89 were included in the control group. Baseline participant characteristics are presented in Table 1.

Throughout the intervention period, a total of 15,327 daily step count data points were collected. Observed data points per experimental group per time point are presented in Appendix Table 1 (available online). Given the study duration and the number of participants, the total possible number of data points was 51,366. Therefore, the collected data points represent approximately 30% of the total possible data points. This level of adherence highlights the challenges in ensuring consistent app usage in real-world settings, which will be further addressed in the Discussion. The proportion of days with recorded steps was similar for the intervention (29.9%) and control group (29.8%), indicating comparable levels of app use adherence across both groups. Over time, the frequency of missing step counts increased in both experimental groups, comprising both intermittent absences and losses due to dropouts. While mixed models accommodate missing data, the implications of this will be reviewed in the Discussion.

A mixed model analysis was conducted to evaluate whether SNapp's coaching content influenced daily step counts in comparison to a control condition. Results showed that the intervention did not significantly affect step counts on average over time (B=−202.30, 95% CI= −889.7, 485.1). Additionally, no statistically significant differences in step counts were observed at individual time points during the intervention, with the exception of the final time point, which will be addressed in the Discussion. The median step counts and on average differences between experimental groups per time point are detailed in Table 2.

It was additionally investigated whether user perceptions influenced the effect of the intervention on daily step counts. The results indicated no significant interaction effect between the experimental group and perceived ease of use ($B_{\text{group} \times \text{perceived ease of use}}$=38.60, 90% CI= −276.5, 353.7). For perceived usefulness, there was a significant interaction effect ($B_{\text{group} \times \text{perceived usefulness}}$ =344.38, 90% CI=40.4, 648.3). To visualize the trend of step counts on average over time in relation to perceived usefulness, participants were classified into groups with low (scoring ≤4, n=115, M=2.17, SD=1.15) or high levels of perceived usefulness (scoring >4, n=61, M=5.44, SD=0.85). There were no statistically significant differences in demographic characteristics between the two groups.

Figure 2 illustrates these trends. In the low perceived usefulness group, both control and intervention groups showed similar step count trends initially, but from the sixth time point, the intervention group's step count decreased compared to the control group. For participants with low perceived usefulness, the median step count was 3,636 [IQR: 3,524] in the intervention group and 4,368 [IQR: 4,402] in the control group, with a median difference of −732 steps (90% CI= −100.4, 2,519.7). Conversely, in the high perceived usefulness group, the intervention

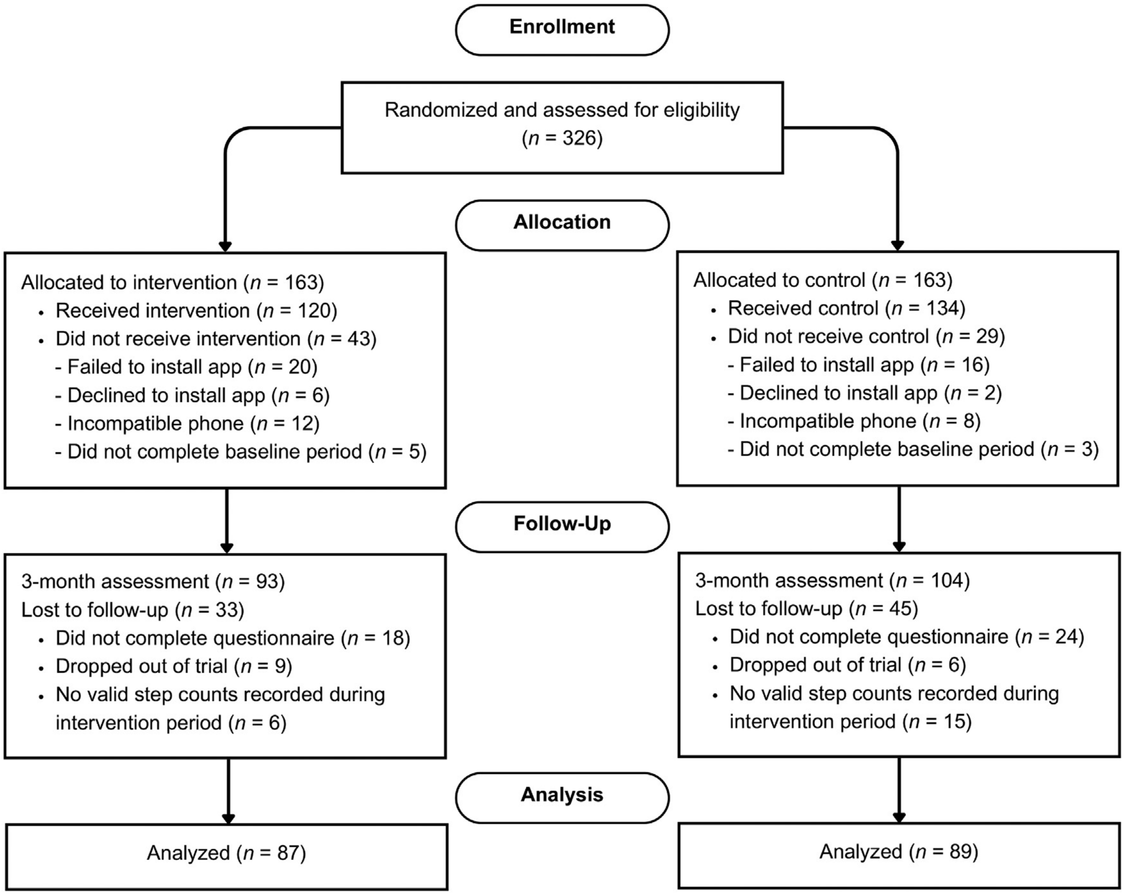

Figure 1. Flow diagram of participants in the SNapp intervention.

group consistently outperformed the control group in terms of step counts throughout the intervention period. For participants with high perceived usefulness, the median step count was 5,218 [IQR: 4,687] in the intervention group and 3,958 [IQR: 3,032] in the control group, with a median difference of 1,260 steps (90% CI: −3,243.7, 1,298.2). However, these median differences were not statistically significant.

Table 1. Baseline Characteristics of SNapp Participants

Characteristics	Total (*N*=176)	Intervention (*n*=87)	Control (*n*=89)	*p*
Age (years), M (SD)	56.4 (10.9)	55.2 (11.0)	57.5 (10.6)	0.161
Gender (female), *n* (%)	134 (76.1)	69 (79.3)	65 (73.0)	0.395
Educational level, *n* (%)				0.985
Low	2 (1.1)	1 (1.1)	1 (1.1)	
Medium	98 (55.7)	49 (56.3)	49 (55.1)	
High	76 (43.2)	37 (42.5)	39 (43.8)	
Operating system, *n* (%):				0.165
Android	118 (67.0)	54 (62.1)	64 (71.9)	
iOS	58 (33.0)	33 (37.9)	25 (28.1)	
Sensor type, *n* (%):				0.065
Step detector	20 (11.4)	6 (6.9)	14 (15.7)	
Step counter	156 (88.6)	81 (93.1)	75 (84.3)	
Baseline daily step count, median [IQR]	3,594 [3,431]	3,605 [3,400]	3,512 [3,905]	0.612

Note: Low educational level: no education and primary education; medium educational level: secondary educational attainments; high educational level: tertiary educational attainments.

Table 2. Median Daily Step Counts and Average Differences Between Experimental Groups per Time Point

Time point	Step count, median [IQR] (intervention, *n*=87)	Step count, median [IQR] (control, *n*=89)	Between-group difference (B [95% CI])
1	3,864 [6,465–2,567]	4,149 [6,401–2,872]	−419.62 [−1,154.5, 315.3]
2	3,893 [6,494–2,596]	3,820 [6,071–2,543]	−61.32 [−812.7, 690.1]
3	4,100 [6,701–2,803]	3,942 [6,193–2,665]	23.54 [−741.2, 788.3]
4	4,284 [6,885–2,987]	3,707 [5,959–2,430]	442.36 [−350.2, 1,234.9]
5	4,524 [7,125–3,227]	4,063 [6,315–2,786]	326.08 [−523.4, 1,175.5]
6	4,177 [6,779–2,881]	3,836 [6,088–2,559]	207.07 [−680.9, 1,095.1]
7	3,740 [6,342–2,444]	3,767 [6,019–2,490]	−161.44 [−1,032.6, 709.7]
8	3,424 [6,026–2,128]	3,778 [6,029–2,501]	−488.00 [−1,366.9, 390.9]
9	3,527 [6,128–2,230]	4,076 [6,328–2,799]	−684.27 [−1,538.9, 170.4]
10	3,870 [6,471–2,573]	4,299 [6,550–3,022]	−563.28 [−1,426.8, 300.2]
11	4,029 [6,630–2,732]	4,418 [6,670–3,141]	−523.88 [−1,410.8, 363.1]
12	4,355 [6,956–3,058]	4,835 [7,086–3,558]	−614.06 [−1,532.6, 304.4]
13	3,098 [5,700–1,802]	4,581 [6,833–3,304]	**−1,617.33 [−2,582.7, −652.0]**

Note: Boldface indicates statistical significance ($p<0.05$).

Nevertheless, the results from the mixed model analysis indicated a significant interaction effect between the experimental group and perceived usefulness on step counts. This suggests that the intervention had a significantly moderated effect on daily step counts, being more effective on average over time for participants with higher levels of perceived usefulness compared to those with lower levels of perceived usefulness. While trends in median step counts align with this finding, the median differences were not statistically significant, indicating that individual variations play a crucial role in the intervention's overall impact.

DISCUSSION

The first objective was to evaluate the effectiveness of SNapp, a JITAI aiming to stimulate walking by using smartphone sensors to collect step count data and provide dynamically tailored coaching content. This study examined whether the addition of SNapp's JITAI elements was more effective in increasing daily step counts compared to a control condition using a self-monitoring app. The second objective was to investigate whether the app's perceived ease of use and usefulness moderated intervention effects. Findings showed that while SNapp

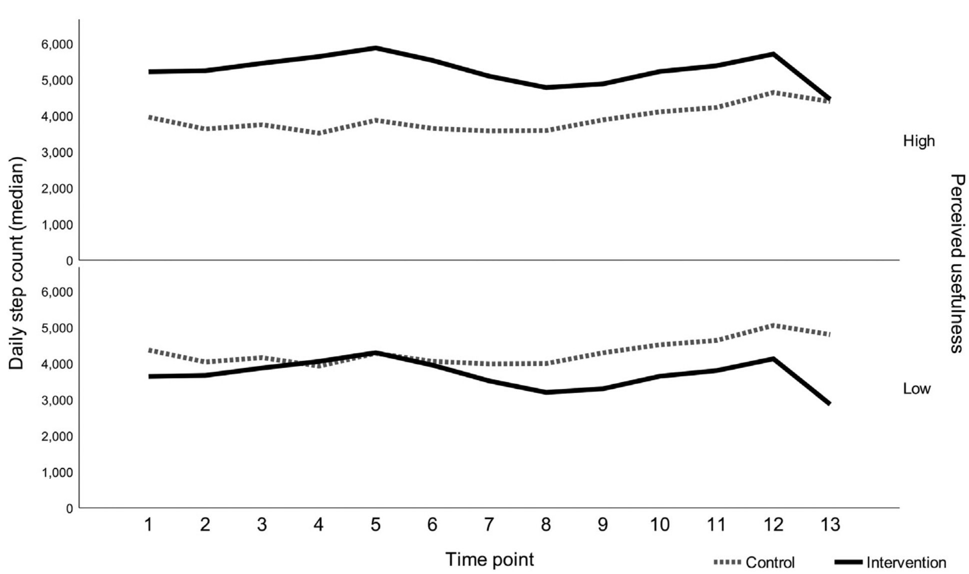

Figure 2. Daily step counts on average over time per experimental group and perceived usefulness group.

did not have a statistically significant main effect, it's JITAI-elements proved more effective in increasing step count compared to a control condition for participants with higher levels of perceived usefulness, but not for participants with lower levels of perceived usefulness.

These findings extend research showing that perceived usefulness positively influences app adoption and intention to continue using apps.[23−25] This study shows that perceived usefulness is also an important factor influencing behavioral effects. Hence, it is essential for apps to be perceived as useful to effectively improve users' activity levels. A key question is what determines whether users find an app useful. On the one hand, perceived usefulness likely depends on offered functionalities. On the other hand, perceived usefulness may also depend on user characteristics such as health consciousness and motivation to achieve activity goals.[36] Additionally, social determinants of health, like economic stability and the built environment,[37] significantly impact perceptions of digital health technology. Although SNapp's database included 153 parks, forests, and walking trails near the participants' municipalities, suggesting general safe access to green spaces, personal circumstances likely varied. Factors like limited time availability and ease of accessibility of green spaces might have constrained some participants more than others, affecting the perceived usefulness of the walking app. Future research should explore which factors most influence usefulness perceptions of PA apps.

Results showed that SNapp's JITAI elements had no statistically significant main effect on daily step counts on average over time compared to a control condition. This lack of a main intervention effect may be explained by the fact that this study compared the effect of SNapp's JITAI elements to a control condition using an app that enabled participants to self-monitor step counts. Hence, the control condition included one behavioral change technique that was also embedded in the intervention condition. Previous research has shown that self-monitoring is one of the most effective strategies for increasing PA.[38−40] Therefore, the use of a self-monitoring app could have influenced the activity levels of participants in the control group and may explain why no significant overall effect was found.

Additionally, the possibility that the lack of a significant main effect might be explained by a lack of exposure to SNapp's coaching content cannot be ruled out. Limitations of this study include the inability to check the extent to which participants read the coaching messages and relatively low app use adherence rates. Factors such as participant burden and preferences for other PA types may have contributed to this low adherence. Lack of long-term user engagement is an issue that has been reported before,[41,42] and can considerably limit app impact. Moreover, higher perceived usefulness could correlate with longer wear time and subsequently higher step counts, suggesting that the observed interaction effect might be due to higher usage adherence, rather than genuinely higher activity levels. However, this study could not capture running time of the app, which is a limitation in assessing true engagement and its effect on step counts. Future work needs to consider these limitations by tracking app usage statistics and implementing strategies to enhance engagement.[43] Practical approaches could include implementing analytics to monitor user interactions with the app, such as message open rates, device wear time, and time spent on app features. To enhance engagement, future studies could consider using reminders and incentives. Additionally, in-app surveys could be used to assess user satisfaction and identify reasons for app (non-)use. Future research is needed to identify ways to improve app engagement in the long term.[44]

Lastly, findings showed no significant interaction effect between experimental group and perceived ease of use. This can be explained by overall high levels of smartphone ownership and digital proficiency in Dutch adults,[45,46] which engenders increasing experience with apps. Previous research has identified conditions under which perceived ease of use is more or less important in influencing technology use.[47] For example, for more experienced user groups and less complex mobile technologies perceived ease of use is not the most influential factor. Other user perceptions may play a greater role, such as perceived enjoyment, which is the extent to which technology use is perceived as enjoyable in its own right.[48] Future studies should examine other user perceptions to improve understanding of the factors influencing app use and health behaviors.

Limitations

This study has limitations. Firstly, the recruitment strategy, aimed at diverse socioeconomic inclusion by engaging participants from socially disadvantaged areas, primarily attracted highly educated individuals. This constrains the generalizability of the intervention's effectiveness to a low-SEP demographic. Consequently, future research should employ more far-reaching recruitment strategies to better represent low-SEP population segments. Future studies could consider including more diverse venues to recruit participants such as public libraries, faith-based organizations, and community centers.[49] Additionally, future research should consider sampling through interpersonal contacts and opinion leader outreach to better reach those of lower SEP.[49]

Secondly, while mixed models provide unbiased estimates if data are missing (completely) at random (MCAR or MAR), missing data may bias estimates if missing not at random.[35] Real-life longitudinal datasets inherently contain a mix of missing data mechanisms that cannot be fully disentangled.[35] This study acknowledges this limitation, noting that while MAR is assumed, this assumption may not hold, potentially impacting validity. This might explain stable step counts during the intervention, followed by a drop at the final time point, particularly for the intervention group (Figure 2). Future research should address missing data and potential missing not at random mechanisms.

Thirdly, although the validity of the app was acceptable, its accuracy can be improved. In line with studies regarding the accuracy of step counter apps,[50−53] the app was found to sometimes underestimate step counts, mainly because it required users to carry their phones on their bodies. The correlation between the step counts recorded by the app and those measured by the ActiGraph accelerometer was lower than the ideal standard in validation studies.[54] While the app's measurements were not perfect, they were deemed sufficient for detecting relative differences between groups in this real-world intervention. However, inaccurate step counts could lead to misinformed tailored feedback. Enhancing measurement accuracy is therefore essential, and app developers should prioritize this. Researchers, too, are advised to assess the validity of apps before their deployment in interventions.

Fourthly, SNapp's development was conducted without user feedback on perceived ease of use and usefulness. This is a limitation, as the findings indicate that apps need to be perceived as useful to foster behavioral effects. Given SNapp's relatively low usefulness scores, it is advisable for developers to use an iterative process with shorter cycles of designing and testing components. This approach allows early resolution of issues, improving adoption and continuous use. Involving the target population during these cycles (e.g., using co-design principles[55]) is recommended. Additionally, incorporating qualitative and mixed-methods research during development can help evaluate user perceptions and ensure the intervention is well-received.

Lastly, the study's design allowed testing the effects of the complete intervention but not the effects of single intervention components. Future research should investigate the efficacy of individual intervention components by, for example, conducting micro-randomized trials that repeatedly randomize participants to different JITAI versions or vary the presence and absence of intervention components.[56]

CONCLUSIONS

This study showed that SNapp's JITAI elements only had a significant positive effect on daily step count on average over time compared to a control condition for participants with higher levels of perceived usefulness, but not for participants with lower levels of perceived usefulness. Based on these findings, it can be concluded that JITAIs have the potential to effectively stimulate PA, provided they are considered beneficial by their users. App developers and intervention researchers are therefore advised to consider user perceptions regarding usefulness during the development of new apps and JITAIs.

ACKNOWLEDGMENTS

We thank all study participants for their efforts. In addition, we thank the members of the Supreme Nudge consortium and its scientific advisory board for their valuable input and advises during the trial conception phase and its execution.

Funding: This study was part of the "Sustainable Prevention of Cardiometabolic Risk through Nudging Health Behaviours" (Supreme Nudge) project. The Supreme Nudge project is funded by the Dutch Heart Foundation (grant number CVON2016-04) and the Netherlands Organization for Health Research and Development (ZonMw) (531003001). Funders had no role in study design; collection, analysis, and interpretation of data; writing the manuscript; and the decision to submit the manuscript for publication.

Declaration of interests: The authors declare that they have no competing interests. No financial disclosures were reported by the authors of this article.

CREDIT AUTHOR STATEMENT

Anne L. Vos: Conceptualization, Methodology, Formal analysis, Investigation, Writing − original draft, Writing − review & editing. Gert-Jan de Bruijn: Conceptualization, Methodology, Supervision, Writing − review & editing. Michel C.A. Klein: Conceptualization, Methodology, Supervision, Writing − review & editing. Sophie C. Boerman: Conceptualization, Methodology, Supervision, Writing − review & editing. Josine M. Stuber: Conceptualization, Methodology, Investigation, Writing − review & editing. Edith G. Smit: Conceptualization, Methodology, Supervision, Writing − review & editing.

SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2024.09.010.

REFERENCES

1. Anzuini F, Battistella A, Izzotti A. Physical activity and cancer prevention: a review of current evidence and biological mechanisms. *J Prev Med Hyg*. 2011;52:174–180. https://doi.org/10.15167/2421-4248/jpmh2011.52.4.288.

2. Laaksonen DE, Lindström J, Lakka TA, et al. Physical activity in the prevention of type 2 diabetes: the finnish diabetes prevention study. *Diabetes.* 2005;54(1):158–165. https://doi.org/10.2337/diabetes.54.1.158.
3. Lee IM, Shiroma EJ, Lobelo F, et al. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. *The Lancet.* 2012;380(9838):219–229. https://doi.org/10.1016/S0140-6736(12)61031-9.
4. Murtagh EM, Nichols L, Mohammed MA, et al. The effect of walking on risk factors for cardiovascular disease: an updated systematic review and meta-analysis of randomised control trials. *Prev Med (Baltim).* 2015;72:34–43. https://doi.org/10.1016/j.ypmed.2014.12.041.
5. Fontán-Vela M, Rivera-Navarro J, Gullón P, et al. Active use and perceptions of parks as urban assets for physical activity: a mixed-methods study. *Health Place.* 2021;71:102660. https://doi.org/10.1016/j.healthplace.2021.102660.
6. Lee RE, Cubbin C, Winkleby M. Contribution of neighbourhood socioeconomic status and physical activity resources to physical activity among women. *J Epidemiol Community Health (1978).* 2007;61:882–890. https://doi.org/10.1136/jech.2006.054098.
7. Wen M, Zhang X. Health promoting community design: contextual effects of built and social environments of urban neighborhoods on exercise: a multilevel study in Chicago. *Am J Health Promot.* 2009;23(4):247–254. https://doi.org/10.4278/ajhp.07052448.
8. Bretthauer M, Kalager M. Disparities in preventive health services: targeting minorities and majorities. *Ann Intern Med.* 2020;172(4):287–288. https://doi.org/10.7326/M19-3899.
9. Nelson HD, Cantor A, Wagner J, et al. Achieving health equity in preventive services: a systematic review for a national institutes of health pathways to prevention workshop. *Ann Intern Med.* 2020;172(4):258–271. https://doi.org/10.7326/M19-3199.
10. Morris JN, Hardman AE. Walking to health. *Sports Med.* 1997;23(5):306–332. https://doi.org/10.2165/00007256-199723050-00004.
11. Oja P, Kelly P, Murtagh EM, et al. Effects of frequency, intensity, duration and volume of walking interventions on CVD risk factors: a systematic review and meta-regression analysis of randomised controlled trials among inactive healthy adults. *Br J Sports Med.* 2018;52:769–775. https://doi.org/10.1136/bjsports-2017-098558.
12. Domin A, Spruijt-Metz D, Theisen D, Ouzzahra Y, Vögele C. Smartphone-based interventions for physical activity promotion: scoping review of the evidence over the last 10 years. *JMIR Mhealth Uhealth.* 2021;9(7):e24308. https://doi.org/10.2196/24308.
13. Lyons E, Lewis Z, Mayrsohn B, Rowland J. Behavior change techniques implemented in electronic lifestyle activity monitors: a systematic content analysis. *J Med Internet Res.* 2014;16(8):e192. https://doi.org/10.2196/jmir.3469.
14. Feter N, dos Santos TS, Caputo EL, da Silva MC. What is the role of smartphones on physical activity promotion? A systematic review and meta-analysis. *Int J Public Health.* 2019;64:679–690. https://doi.org/10.1007/s00038-019-01210-7.
15. Hardeman W, Houghton J, Lane K, Jones A, Naughton F. A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *Int J Behav Nutr Phys Act.* 2019;16:31. https://doi.org/10.1186/s12966-019-0792-7.
16. 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(6):446–462. https://doi.org/10.1007/S12160-016-9830-8.
17. Thomas Craig KJ, Morgan LC, Chen CH, et al. Systematic review of context-aware digital behavior change interventions to improve health. *Transl Behav Med.* 2021;11(5):1037–1048. https://doi.org/10.1093/tbm/ibaa099.
18. Wang L, Miller LC. Just-in-the-moment adaptive interventions (JITAI): a meta-analytical review. *Health Commun.* 2020;35(12):1531–1544. https://doi.org/10.1080/10410236.2019.1652388.
19. Vos AL, De Bruijn GJ, Klein MC, et al. SNapp, a tailored smartphone app intervention to promote walking in adults of low socioeconomic position: development and qualitative pilot study. *JMIR Form Res.* 2023;7:e40851. https://doi.org/10.2196/40851.
20. Stuber JM, Mackenbach JD, De Boer FE, et al. Reducing cardiometabolic risk in adults with a low socioeconomic position: protocol of the Supreme Nudge parallel cluster-randomised controlled supermarket trial. *Nutr J.* 2020;19(1):46. https://doi.org/10.1186/s12937-020-00562-8.
21. Stuber JM, Mackenbach JD, de Boer FE, et al. Correction: reducing cardiometabolic risk in adults with a low socioeconomic position: protocol of the Supreme Nudge parallel cluster-randomised controlled supermarket trial. *Nutr J.* 2022;21(1):44. https://doi.org/10.1186/s12937-022-00795-9.
22. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 1989;13(3):319–339. https://doi.org/10.2307/249008.
23. Beldad AD, Hegner SM. Expanding the Technology Acceptance Model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users' willingness to continue using a fitness app: a structural equation modeling approach. *Int J Hum Comput Interact.* 2018;34(9):882–893. https://doi.org/10.1080/10447318.2017.1403220.
24. Cho H, Chi C, Chiu W. Understanding sustained usage of health and fitness apps: incorporating the technology acceptance model with the investment model. *Technol Soc.* 2020;63:101429. https://doi.org/10.1016/j.techsoc.2020.101429.
25. Cho J. The impact of post-adoption beliefs on the continued use of health apps. *Int J Med Inform.* 2016;87:75–83. https://doi.org/10.1016/j.ijmedinf.2015.12.016.
26. Lakerveld J, Mackenbach JD, De Boer F, et al. Improving cardiometabolic health through nudging dietary behaviours and physical activity in low SES adults: design of the Supreme Nudge project. *BMC Public Health.* 2018;18:899. https://doi.org/10.1186/s12889-018-5839-1.
27. Stuber JM, Mackenbach JD, de Bruijn GJ, et al. Real-world nudging, pricing, and mobile physical activity coaching was insufficient to improve lifestyle behaviours and cardiometabolic health: the Supreme Nudge parallel cluster-randomised controlled supermarket trial. *BMC Med.* 2024;22:52. https://doi.org/10.1186/s12916-024-03268-4.
28. Stuber JM, Van Hoek BACE, Vos AL, et al. Participant recruitment, baseline characteristics and at-home-measurements of cardiometabolic risk markers: insights from the Supreme Nudge parallel cluster-randomised controlled supermarket trial. *Trials.* 2023;24:159. https://doi.org/10.1186/s13063-023-07157-8.
29. Central Bureau for Statistics. Socio-economic status; scores by neighborhood and district, regional classification 2021. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/85163NED/table?ts=1649329891546 2022. Accessed February 14, 2023.
30. Craig CL, Tudor-Locke C, Cragg S, Cameron C. Process and treatment of pedometer data collection for youth: the Canadian physical activity levels among youth study. *Med Sci Sports Exerc.* 2010;42(3):430–435. https://doi.org/10.1249/mss.0B013E3181B67544.
31. Fukushima N, Inoue S, Hikihara Y, et al. Pedometer-determined physical activity among youth in the Tokyo metropolitan area: a cross-sectional study. *BMC Public Health.* 2016;16:1104. https://doi.org/10.1186/s12889-016-3775-5.
32. Rowe DA, Mahar MT, Raedeke TD. Measuring physical activity in children with pedometers: reliability, reactivity, and replacing missing data. *Pediatr Exerc Sci.* 2004;16(4):343–354. https://doi.org/10.1123/pes.16.4.343.
33. Tudor-Locke C, Giles-Corti B, Knuiman M, McCormack G. Tracking of pedometer-determined physical activity in adults who relocate: results from RESIDE. *Int J Behav Nutr Phys Act.* 2008;5:39. https://doi.org/10.1186/1479-5868-5-39.

34. Davis FD, Bagozzi RP, Warshaw PR. User acceptance of computer technology: a comparison of two theoretical models. *Manage Sci.* 1989;35(8):982–1003. https://doi.org/10.1287/mnsc.35.8.982.
35. Twisk J, De Boer M, De Vente W, Heymans M. Multiple imputation of missing values was not necessary before performing a longitudinal mixed-model analysis. *J Clin Epidemiol.* 2013;66(9):1022–1028. https://doi.org/10.1016/j.jclinepi.2013.03.017.
36. Carroll JK, Moorhead A, Bond R, et al. Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *J Med Internet Res.* 2017;19(4):e125. https://doi.org/10.2196/jmir.5604.
37. Anil Kumar Vaidhyam S, Huang K. Social determinants of health and patients' technology acceptance of telehealth during the COVID-19 pandemic: pilot survey. *JMIR Hum Factors.* 2023;10:e47982. https://doi.org/10.2196/47982.
38. Belmon LS, Middelweerd A, Te Velde SJ, Brug J. Dutch young adults ratings of behavior change techniques applied in mobile phone apps to promote physical activity: a cross-sectional survey. *JMIR Mhealth Uhealth.* 2015;3(4):e103. https://doi.org/10.2196/mhealth.4383.
39. Knittle K, Nurmi J, Crutzen R, et al. How can interventions increase motivation for physical activity? A systematic review and meta-analysis. *Health Psychol Rev.* 2018;12(3):211–230. https://doi.org/10.1080/17437199.2018.1435299.
40. Olander EK, Fletcher H, Williams S, et al. What are the most effective techniques in changing obese individuals' physical activity self-efficacy and behaviour: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act.* 2013;10:29. https://doi.org/10.1186/1479-5868-10-29.
41. Amagai S, Pila S, Kaat AJ, Nowinski CJ, Gershon RC. Challenges in participant engagement and retention using mobile health apps: literature review. *J Med Internet Res.* 2022;24(4):e35120. https://doi.org/10.2196/35120.
42. Schoeppe S, Alley S, Van Lippevelde W, et al. Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: a systematic review. *Int J Behav Nutr Phys Act.* 2016;13:127. https://doi.org/10.1186/s12966-016-0454-y.
43. O'Brien HL, Morton E, Kampen A, Barnes SJ, Michalak EE. Beyond clicks and downloads: a call for a more comprehensive approach to measuring mobile-health app engagement. *BJPsych Open.* 2020;6(5):e86. https://doi.org/10.1192/bjo.2020.72.
44. Serrano KJ, Coa KI, Yu M, Wolff-Hughes DL, Atienza AA. Characterizing user engagement with health app data: a data mining approach. *Transl Behav Med.* 2017;7(2):277–285. https://doi.org/10.1007/s13142-017-0508-y.
45. Central Bureau for Statistics. The Netherlands ranks among the EU top in digital skills. https://www.cbs.nl/en-gb/news/2020/07/the-netherlands-ranks-among-the-eu-top-in-digital-skills. 2020. Accessed February 14, 2023.
46. Central Bureau for Statistics. Internet; access, use and facilities; 2012-2019. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83429NED/table?ts=1539774264847. 2019. Accessed February 14, 2023.
47. Sun H, Zhang P. The role of moderating factors in user technology acceptance. *Int J Hum Comput Stud.* 2006;64(2):53–78. https://doi.org/10.1016/j.ijhcs.2005.04.013.
48. Davis FD, Bagozzi RP, Warshaw PR. Extrinsic and intrinsic motivation to use computers in the workplace. *J Appl Soc Psychol.* 1992;22(14):1111–1132. https://doi.org/10.1111/J.1559-1816.1992.TB00945.X.
49. Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions can worsen inequality. *JAMIA.* 2018;25(8):1080–1088. https://doi.org/10.1093/jamia/ocy052.
50. Amagasa S, Kamada M, Sasai H, et al. How well iPhones measure steps in free-living conditions: cross-sectional validation study. *JMIR Mhealth Uhealth.* 2019;7(1):e10418. https://doi.org/10.2196/10418.
51. Bergman RJ, Spellman JW, Hall ME, Bergman SM. Is there a valid app for that? Validity of a free pedometer iPhone application. *J Phys Act Health.* 2012;9(5):670–676. https://doi.org/10.1123/jpah.9.5.670.
52. Duncan MJ, Wunderlich K, Zhao Y, Faulkner G. Walk this way: validity evidence of iPhone health application step count in laboratory and free-living conditions. *J Sports Sci.* 2018;36(15):1695–1704. https://doi.org/10.1080/02640414.2017.1409855.
53. Funk MD, Salazar CL, Martinez M, et al. Validity of smartphone applications at measuring steps: does wear location matter? *J Meas Phys Behav.* 2019;2(1):22–27. https://doi.org/10.1123/jmpb.2018-0025.
54. Evenson KR, Goto MM, Furberg RD. Systematic review of the validity and reliability of consumer-wearable activity trackers. *Int J Behav Nutr Phys Act.* 2015;12:159. https://doi.org/10.1186/s12966-015-0314-1.
55. Fox S, Brown LJE, Antrobus S, et al. Co-design of a smartphone app for people living with dementia by applying agile, iterative co-design principles: development and usability study. *JMIR Mhealth Uhealth.* 2022;10(1):e24483. https://doi.org/10.2196/24483.
56. Klasnja P, Hekler EB, Shiffman S, et al. Microrandomized trials: an experimental design for developing just-in-time adaptive interventions. *Health Psychol.* 2015;34:1220–1228. https://doi.org/10.1037/hea0000305.