EFFECTS OF A MOBILE HEALTH INTERVENTION ON HEALTH-RELATED OUTCOMES IN JAPANESE OFFICE WORKERS: A PILOT STUDY

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Abstract

Objectives: The purpose of the current study was to explore the effects of a mobile health (mHealth) intervention based on the Persuasive System Design (PSD) model on health-related outcomes among office workers. **Material and Methods:** The authors conducted a trial that consisted of a 4-week baseline and an 8-week intervention period by reference to 23 office workers in a private research company. The mHealth application was developed to improve these workers' daily step count, decrease their sedentary time, and increase their sleep duration in accordance with the PSD model. The app features included at least 1 principal factor from each of the 4 main categories of the PSD model (primary task support, dialogue support, system credibility support, and social support). The objective health-related variables were measured using a smartwatch (Fitbit Luxe) that was synchronized with the application using the Fitbit Web Application Programming Interface. Subjects used the app, which included self-monitoring, personalized messages, education, and a competition system for users, during the intervention period. **Results:** Sedentary time exhibited a significant decrease (a median reduction of 14 min/day, p < 0.05) during the intervention period. No significant differences in daily step count and sleep duration were observed between the baseline and intervention periods. **Conclusions:** This study suggests that the mHealth intervention based on the PSD model was useful for reducing sedentary time among office workers. Given that many previous studies on this topic have not been based on any theories, future studies should investigate the impact of structured selection behavior change theories on health-related outcomes among office workers. Int J Occup Med Environ Health. 2024;37(2)

Key words:
exercise, sleep duration, telemedicine, behavior therapy, sedentary time, wearable electronic devices

INTRODUCTION

Physical inactivity is one of the major social problems facing the developed world because of its wide-ranging negative effects, such as increasing the risk of noncommunicable diseases (e.g., cardiovascular diseases, cancer, and diabetes) [1]. Office workers are typically sedentary during the day and are therefore prone to inadequate physical activity levels [2]. Furthermore, many companies have introduced remote work due to the COVID-19 pandemic. It is reasonable to expect that remote work leads to severe levels of sedentary behavior because physical activity due to commuting and working is reduced. Prior research showed that up to 67% of office workers curtailed their physical activity levels owing to remote work [3]. The adverse ramifications of sedentary behavior have also attracted much attention in recent years. Notably, the World Health Organization recommends that adults should limit the amount of time spent being sedentary [4]. Furthermore, inactivity is believed to exert an adverse influence on sleep duration [5].

Objective health-related variables, including daily step count, sedentary time, and sleep duration, can be measured by commercial wearable devices (e.g., Fitbit, Garmin, Oura Ring). It is well known that objective health-related variables are closely related to health outcomes. A meta-analysis investigated the relationship between daily step count and all-cause mortality, which showed a progressively decreasing risk among adults <60 years old with a daily step count up to 8000–10 000 steps/day [6]. Another study investigated the relationship between sedentary time and all-cause mortality and showed a log-linear dose–response association [7]. In particular, the cutoff value of device-based sedentary time was 9 h/day (540 min/day). Regarding sleep duration, a previous study involving >300 000 adults found that both men and women who slept 7 h/day had the lowest risk for all-cause cardiovascular disease and other-cause mortality compared to their peers [8].

Mobile health (mHealth) technology has become increasingly popular around the world. Nevertheless, a limited number of studies have evaluated the effects of mHealth interventions on objective health-related outcomes in office workers. In the context of physical activity, a recent systematic review and meta-analysis study suggested that mHealth interventions are effective for improving physical activity among workers. [9]. On the other hand, the results of previous studies regarding objective measures of sedentary time and sleep duration have been insufficient or have yielded inconclusive outcomes [10–12].

Typical mHealth functions encompass goal setting, self-monitoring, and feedback, offer the benefit of minimizing human costs and can be carried out remotely. Although positive effects on some objective variables were reported, many previous studies offered financial incentives to subjects as a reward for improvement [13,14]. While financial incentives are effective in the short-term, the financial burden is high, and the effect on long-term

health is questionable [15]. Therefore, mHealth interventions without financial incentives would be preferable from not only the health promotion perspective of companies but also the long-term health perspective of users.

The purpose of this pilot study was to explore the effects of a mHealth intervention based on the Persuasive Systems Design (PSD) model [16] on health-related outcomes among office workers. The authors' app features included at least 1 principal factor from each of the 4 main categories of the PSD model (primary task support, dialogue support, system credibility support, and social support). The present study was also unique in that it did not rely on a financial incentive.

MATERIAL AND METHODS
Experimental design

The current study used a single-group, pre-post pilot design at a private research company in Japan. The experiment was also a part of the company's health management policy. The research team consisted of employees of the same company, including app developers and health experts; no participants were drawn from outside the company. The experiment was conducted remotely, and there were no face-to-face meetings between the research team and the subjects. All subjects participated in the 4-week baseline period and the 8-week intervention period. Not all subjects started at the same time, which resulted in start dates ranging September–December 2022.

Subjects

All company staff, including full-time employees, part-time employees, and temporary employees (approx. 300), were informed about the experiment by advertising brochures sent via e-mail and internal company networking services. Interested employees could attend a web briefing that included information on the purpose and method of the experiment and a short lecture on physical activity. The research team stated that participation in the experiment was not related

to internal personal evaluations in the company. All subjects were volunteers and received no financial incentive for their participation in the experiment.

In the present study, office workers were defined as individuals working in an office environment whose main tasks involved using a computer, reading, talking on the telephone, making presentations, and participating in meetings [17]. In addition, the inclusion criteria of the subjects were that they were:

1) healthy (not instructed to restrict any physical activity by a physician),
2) aged 20–65 years,
3) owned an iOS or Android smartphone.

Intervention

All subjects were provided with a Fitbit Luxe smartwatch (Fitbit Inc., San Francisco, CA, USA) and a smartphone app named STEP MORE. The app was developed for the current study and is not commercially available. The app was offered on both Android and iOS smartphones. Each subject installed the app on their personal smartphone. The data from the smartwatch were synchronized via the Fitbit Web Application Programming Interface (API).

The app-based intervention employed the PSD model framework [16], which did not rely on financial incentives. The PSD model is an extended framework for the application of the behavior change theory proposed by Fogg to software requirements [18]. This framework broadly classified 28 persuasive strategies into 4 categories:

– primary task support – this design principle supports users in performing their main tasks; specifically, it includes the persuasive strategies of reduction, tunneling, tailoring, personalization, self-monitoring, simulation, and rehearsal;
– dialogue support – this design principle focuses on providing support in the form of computer-human

dialogue support to help users continue to engage in the target behavior; specifically, it includes the persuasive strategies of praise, rewards, reminders, suggestion, similarity, liking, and social role;
– system credibility support – this design principle enhances the credibility of the system, thereby enhancing its persuasiveness; specifically, it includes the persuasive strategies of trustworthiness, expertise, surface credibility, real-world feel, authority, third-party endorsements, and verifiability;
– social support – this design principle leverages social influence to enhance user motivation; specifically, it includes the persuasive strategies of social facilitation, social comparison, normative influence, social learning, cooperation, competition, and recognition.

The authors selected app features that included at least 1 element from each of these 4 categories of the framework discussed above. The app offers 4 main functions: self-monitoring, education, feedback, and a competition system (Figure 1). With regard to the primary task support category, the self-monitoring and feedback features are relevant. Self-monitoring is a feature pertaining to the graphical visualization of objective health-related variables, corresponding to self-monitoring in the PSD model. Feedback is a feature that requires the research team to send personalized messages to each subject 3 times/week. The messages are created individually based on each user's objective health-related data, thus including elements of personalization. With respect to dialogue support, the app's feedback feature is relevant. The messages sent to each subject include praise for improvements in health-related indicators and suggestions for actions to address indicators that have not improved. These messages include the elements of praise and suggestions in the PSD model. With regard to the system credibility support category, the app's education feature is relevant. Articles about health are written by health experts (Ph.D. degrees in health and sports science) and sent to par-
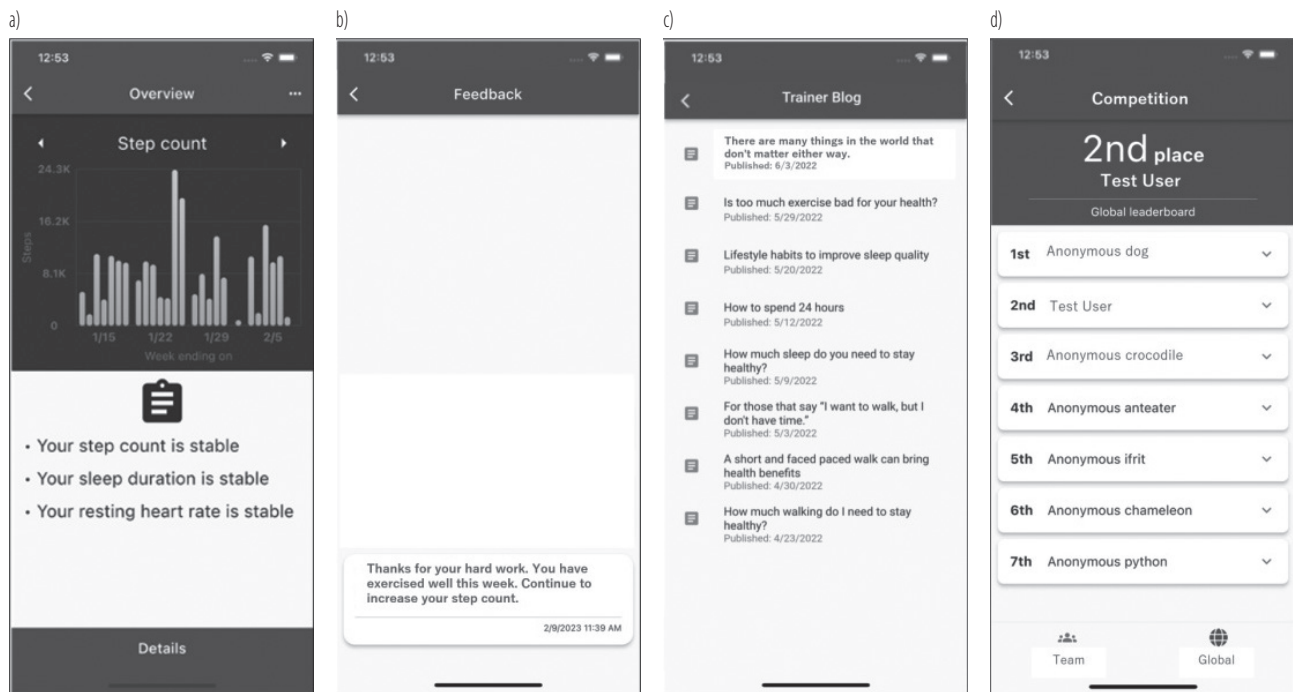
Figure 1. The application screens: a) self-monitoring, b) feedback, c) education, d) competition, the study cohort of office workers, measured in September 2022–March 2023 in daily living environment of Japan

ticipants once a week. Of the 8 articles, 2 focus on daily step counts, 1 focuses on sedentary time, 2 focus on sleep duration, and the remaining 3 focus on multiple variables. By emphasizing the fact that the article delivery is supervised by experts, it includes elements of expertise. Finally, with respect to the social support category, the app's competition system feature is relevant. The research team designs a competition system that assigns higher scores when more steps are taken daily, when sedentary time is less, and when the variation in sleep start time is small. The app automatically calculates the score for each subject's variables and displays individual rankings. The competition feature includes 2 modes. In 1 mode, all participants in the experiment are anonymized (represent by animal names), and in the other mode, subjects form teams with each other (this mode is optional). An important feature is that even if the absolute value of the variable is not good, the user can obtain a high ranking because the relative change (i.e., a comparison with each person's score the previous week) is taken into account. This feature includes elements of competition and social comparison.

During weeks 1–4 (baseline), the subjects used the developed app only to sync the objective data. In other words, the abovementioned functions were unavailable. During weeks 5–12 (intervention), the subjects were instructed to use the app and engage with the features described above.

Measurements

Data on objective health-related variables, including daily step count, sleep duration, and sedentary time, were collected using a Fitbit Luxe smartwatch and the developed app throughout the experimental period. The reason why the authors used daily step count, sleep duration, and sedentary time as the objective health-related variables was that the validity of these variables is higher than that of other detailed variables (e.g., physical activity level as assessed by metabolic equivalents, sleep stage) [19–21].

The subjective health-related variables, including physical activity level, sleep quality, and self-rated health, were collected using a web-based survey. Physical activity was evaluated by the Japanese version of the *International Physical Activity Questionnaire – Short Version* (IPAQ-short version) [22]. General physical activity over the last 7 days was determined based on this survey. Sleep quality was evaluated by the Japanese version of the *Pittsburgh Sleep Quality Index* (PSQI) [23]. The global PSQI score was calculated based on an 18-item constructed questionnaire. Higher scores indicated poorer subjective sleep quality. Self-rated health was evaluated by a 5-point Likert-type scale ranging from 1 (worst) to 5 (best). The subjective variables were assessed at weeks 0 (before baseline), 4 (after baseline), 8 (middle of the intervention), and 12 (after the intervention).

Statistical analysis

Data preprocessing and statistical analyses were performed using Python software (v. 3.10.10). The packages pandas and scipy were used for data processing and statistical analysis, respectively. The daily step count was considered valid if the value was >500 steps/day [24]. Valid subjects were defined as those with at least 80% valid days for daily step count throughout the experimental period. The source of invalid days could be the subject not wearing their smartwatch or a malfunction. Data are expressed as the median (Me) and interquartile range (IQR). The objective health-related variables were averaged for each period. Subjective health-related variables were calculated as the average of 2 survey scores (baseline: weeks 0–4, intervention: weeks 8–12). Subgroup analyses were performed to determine whether the baseline physical activity levels were influenced by the intervention functions. The subjects were categorized into 3 groups according to tertile ranges based on their baseline daily step counts (low, middle, and high groups). The objective and subjective health-related variables were analyzed by

performing Wilcoxon signed-rank tests. Subsequently, the effect size (ES) was calculated to quantify for practical significance. The ES estimator "r" is interpreted as small at 0.1, medium at 0.3, and large at or above 0.5 [25].

Ethics approval statement

The current study was carried out with the approval of the ethics examination of the Research Institute of Human Engineering for Quality Life, Osaka, Japan (E22-2). The study was conducted in accordance with the Declaration of Helsinki, and written consent was obtained from all subjects prior to participation.

RESULTS

Initially, 30 subjects agreed to participate in the experiment, and 7 subjects withdrew due to personal reasons or insufficient data (a lack of daily step count data for >20% of the period) (Figure 2). The 23 subjects who completed the experiment had a Me age of 41.0 (IQR 37.0–45.0) years and a body mass index of Me = 22.9 (IQR 21.2–27.2); in addition, they were mostly male (19 out of 23). Because some subjects did not wear the smartwatch while sleeping (>20%), the number of subjects with data on sleep duration and sedentary time was decreased (18 out of 23 had valid data).

Table 1 shows the results of objective and subjective health-related variables. Sedentary time was significantly decreased during the intervention period compared to the baseline period. There were no significant differences in daily step count, sleep duration, or any subjective health-related variables between the baseline and intervention periods. Figure 3 shows the time course changes in the daily step count throughout the experimental period.

Table 2 shows the results of the subgroup analyses based on daily step count in the baseline period. The daily step count in the baseline period was:
– Me = 6638 (IQR 5316–7423) steps/day for the low group,
– Me = 8710 (IQR 8376–8908) steps/day for the middle group,
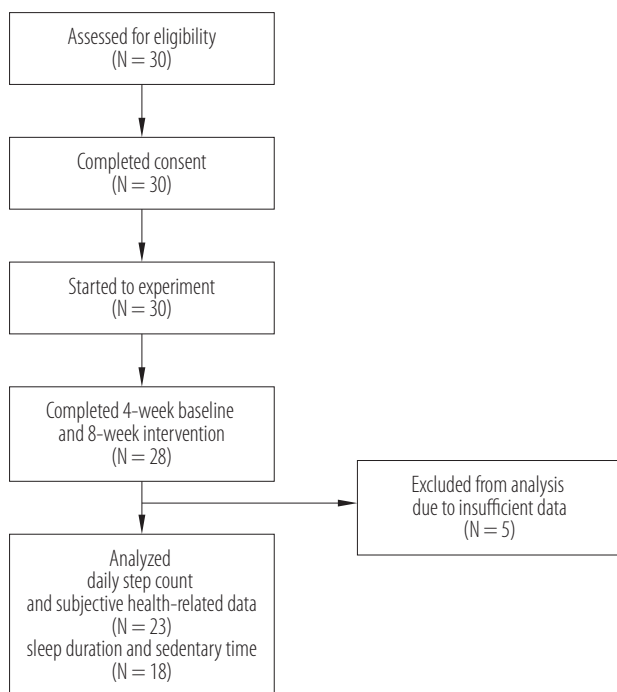
Figure 2. Subject flow throughout the study of office workers, measured in September 2022–March 2023 in daily living environment of Japan

– Me = 10 374 (IQR: 9767–11 085) steps per day for the high group.

These low, middle, and high groups comprised 7, 8, and 8 subjects, respectively. Regarding the subgroup analysis of sedentary time and sleep duration, these groups included 6, 7, and 5 subjects, respectively. For the middle group, sedentary time decreased and sleep duration increased, both of which were found to be statistically significant.

DISCUSSION

The current study explored the effects of an mHealth intervention on health-related outcomes in office workers. The authors found a significant decrease in sedentary time in the intervention period.

The authors implemented the app based on the PSD model. Research on mobile health apps that aim to promote health among office workers based on behavior change theory has been limited. Aldenaini et al. [26] conducted a systematic review of the effectiveness of mobile phone-based persuasive technologies with regard to promoting physical activity and reducing sedentary behavior. In this review, these authors employed the PSD model to analyze persuasive strategies and identified the following as the most effective such strategies: tracking/self-monitoring, personalization, goal setting, reminders, other social support strategies, praise and reduction, social competition, suggestion, social comparison, and tunneling and social cooperation. The majority of these principles are in line with primary task support and dialogue support, but notable gaps are observed with respect to system credibility support and social support. Moreover, Al Ayubiet al. [27] developed a persuasive and social mHealth app that was designed to monitor users' steps and to motivate users to walk more every day. The app on which this previous study focused included primary task support, dialogue support, and social support; however, it did not include system credibility support. In contrast, the authors' pilot study was unique in that the authors designed the app to incorporate the principles of system credibility support and social support. As a result, a significant improvement was observed in sedentary time, as explained in the following paragraph. In the future, it will be necessary to conduct additional research to explore the impact of structured selection behavior change theories on health-related outcomes.

Although many studies have documented that non-mHealth interventions reduced sedentary time [28], it is not clear whether mHealth interventions reduce sedentary time. Bort-Roig et al. [10] investigated the effects of an mHealth intervention on physical activity and sedentary time for desk-based employees while at work and away from work. The intervention increased the number of daily breaks and the time spent on short sedentary bouts (<20 min) but did not change the total sedentary time. Another study was conducted by Boerema et al. [11], investigating office workers before and after an mHealth intervention. They also reported no changes

Table 1. Changes in objective and subjective health-related variables from the baseline to intervention periods of the study cohort of office workers, measured in September 2022–March 2023 in daily living environment of Japan

Variable	Period		Effect size
	baseline	intervention	
Objective			
daily step count [steps/day] (Me (IQR))	8807 (7830–9716)	9067 (7423–9329)	0.22
sedentary time [min/day] (Me (IQR))	754 (715–818)	740 (714–799)*	0.60
sleep duration [min/day] (Me (IQR))	361 (342–378)	367 (336–393)	0.32
Subjective			
general physical activity [MET_{min}/week] (Me (IQR))	808.5 (476.6–1481.0)	834.0 (592.1–1194.3)	0.26
sleep quality (Me (IQR))	5.5 (5.0–9.0)	6.5 (5.0–7.75)	0.25
self-rated health (Me (IQR))	3.0 (3.0–3.5)	3.5 (2.8–4.0)	0.14

The sedentary time and sleep duration analyses included 18 subjects.
The effect size r was derived using the following formula: $r = \sqrt{z^2/N}$, where z represents the test statistic and N represents the sample size.
General physical activity was assessed by the Japanese version of the *International Physical Activity Questionnaire – Short Version* and expressed by metabolic equivalent of task.
Sleep quality was assessed by the Japanese version of the *Pittsburgh Sleep Quality Index* (PSQI) and expressed by the global PSQI score.
Self-rated health was evaluated by a 5-point Likert-type scale ranging from 1 (worst) to 5 (best).
* $p < 0.05$ for within-group changes from baseline to intervention (Wilcoxon signed-rank test).

in the total sedentary time before and after the intervention. Contrary to these previous studies, the current study showed a significant decrease in sedentary time during the intervention period. This finding is intriguing and suggests the effectiveness of mHealth interventions based on the PSD model. The primary app functions highlighting sedentary time (an educational article and being a primary value for the competition system) could potentially be the cause of the positive effect on sedentary time. On the other hand, it seems likely that the larger value of sedentary time in the baseline period of this study compared with previous studies is partially explained by discrepancies in the results. The sedentary time in the present study was higher than the cutoff values the previous studies described in the Introduction section. Additionally, although strict comparisons with previous studies are difficult, compared to the baseline sedentary time of 9.5 h in the study by Bort-Roig et al. [10] discussed above, the current study reported a baseline sedentary time as long as approx. 13 h. Thus, in addition to the function of
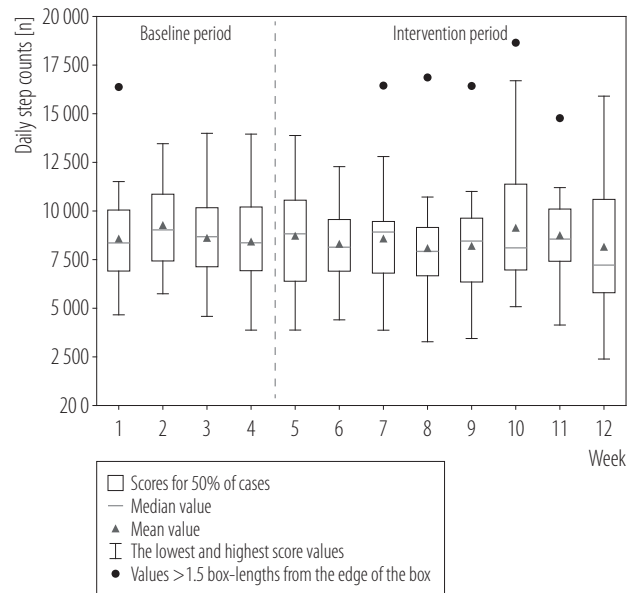
Figure 3. Trends of daily step counts of office workers, measured in September 2022–March 2023 in daily living environment of Japan

the intervention, the longer sedentary time of the subjects may be a significant factor in the effect of the intervention.

Table 2. Changes in objective health-related variables of the group by baseline steps level from the baseline to intervention periods of the study cohort of office workers, measured in September 2022–March 2023 in daily living environment of Japan

Variable	Period		Effect size
	baseline	intervention	
Low group			
daily step count [steps/day] (Me (IQR))	6638 (5316–7423)	6315 (5630–7185)	0.26
sedentary time [min/day] (Me (IQR))	883 (827–892)	886 (818–898)	0.21
sleep duration [min/day] (Me (IQR))	355 (344–373)	348 (336–363)	0.21
Middle group			
daily step count [steps/day] (Me (IQR))	8710 (8376–8908)	9130 (8729–9476)	0.40
sedentary time [min/day] (Me (IQR))	715 (707–753)	714 (670–720)*	0.89
sleep duration [min/day] (Me (IQR))	374 (357–406)	380 (371–418)*	0.89
High group			
daily step count [steps/day] (Me (IQR))	10374 (9767–11085)	9252 (9149–10035)	0.54
sedentary time [min/day] (Me (IQR))	751 (732–799)	757 (718–766)	0.42
sleep duration [min/day] (Me (IQR))	319 (308–371)	310 (310–354)	0.18

The groups were classified based on their daily step counts during the baseline period as follows: low group (Me = 6638 steps/day), middle group (Me = 8710 steps/day), and high group (Me = 10375 steps/day).
The sedentary time and sleep duration analyses included 18 subjects.
The effect size r was derived using the following formula: $r = \sqrt{z^2/N}$, where z represents the test statistic and N represents the sample size.
* p < 0.05 for within-group changes from baseline to intervention (Wilcoxon signed-rank test).

It seems likely that the app design was ineffective in increasing the daily step count because there were no significant changes in the daily step count between the baseline and intervention periods. One of the reasons for the lack of change in the daily step count could be that the daily step counts of the subjects were higher than the expected values. In fact, the mean (M) daily step count (8738 steps/day) meets the requirement for reducing the mortality rate mentioned in the Introduction section. Because this evidence was also presented in the educational article, the subjects might not have been motivated to take more steps. Another possible reason was the ambient temperature during the experiment. According to a previous study of elderly Japanese people, the daily step count is highest when the ambient temperature is M = 17ºC and decreases when it is <17ºC or >17ºC [29]. The start time of the present experiment was October–December, so most of the subjects were entering the winter months during the intervention period, suggesting that the results of the daily step count were masked by the external environment. Overall, the intervention did not produce significant effects that outweighed the influence of temperature. This could be corrected in a future large experiment that includes a control group during the intervention period.

Interestingly, the intervention effects were better for the middle group than for the high and low groups, which is to say that daily step count increased (medium-sized effect, although it did not reach statistical significance), the sedentary time decreased, and the sleep duration increased. These data suggest that an effective intervention approach differs depending on the baseline physical activity level (i.e., daily step counts). Lee et al. [30] investigated the effects of an mHealth intervention among manufacturing

company workers and reported no significant increase in the daily step count for subjects with >10 000 steps/day. Furthermore, most studies that reported an increase in the daily step count with an mHealth intervention targeted subjects who averaged <10 000 steps/day [31–33]. In line with these findings, the high group similarly found no significant effect, likely due to the fact that the subjects' step count exceeded 10 000 steps/day. On the other hand, the reason for the low effectiveness in the low group was likely that the subjects had fewer health concerns. For these subjects, the use of educational content and motivational behavior for health enhancement, as pursued in the present study, might be deemed challenging. There is speculation that expanding the PSD model to include elements of liking in dialogue support and adopting an approach for these subjects that emphasizes non-health-conscious aspects might potentially yield positive outcomes.

It is important to acknowledge the inherent limitations of the present study. One primary limitation of this research was related to the sample size. The present study was a pilot study and included a relatively small sample of employees. While the number of subjects appeared to be adequate for a pilot study according to Hooper [34], it is important to interpret the subgroup analyses with caution. In addition, the authors initially aimed to recruit as many as 45 subjects to account for potential dropouts. However, the actual number of subjects fell short of that target. This situation may indicate a lack of interest in physical activity using mHealth among office workers. In addition, if a large sample is recruited, the effects of ambient temperature and other factors can be considered. The second limitation pertained to the lack of detailed information regarding subject adherence. Due to the specifications of the app, detailed information on the amount of time spent using (viewing) the app was not logged. In the future, a more thorough examination of the intervention effects will be necessary, including an analysis of the relationship between specific app usage patterns and the rate of change in health-related outcomes. The current experiment was conducted using commercial wearable devices (Fitbit) rather than physical activity monitors designed for research, such as the ActiGraph (ActiGraph LLC, Pensacola, FL, USA) and activPAL monitors (PAL Technologies Ltd, Glasgow, UK). However, the data on daily step count, sedentary time, and sleep duration had sufficient validity, unlike more detailed data. On the other hand, several subjects were uncomfortable when wearing the smartwatch while sleeping. Because data from Fitbit's API were allocated to sedentary time when the device was not worn, the number of subjects analyzed regarding sleep duration and sedentary time was small.

CONCLUSIONS

The mHealth intervention based on the PSD model including primary task support, dialogue support, system credibility support, and social support can reduce sedentary time in office workers without the use of a financial incentive. Given that many previous studies on this topic have not been based on any theories, future studies should investigate the impact of structured selection behavior change theories on health-related outcomes among office workers.

Conflict of interest

Takumi Meguro, Hampus Hammarlund, and Masaru Honjo are employees of KDDI Research, Inc. Fuminori Takayama is an invited researcher at KDDI Research, Inc. All authors are receiving salaries from KDDI Research, Inc. KDDI Research, Inc. is a private research company under KDDI Corporation.

Author contributions

Research concept: Takumi Meguro, Fuminori Takayama, Hampus Hammarlund, Masaru Honjo

Research methodology: Takumi Meguro, Fuminori Takayama, Hampus Hammarlund

Collecting material: Takumi Meguro, Fuminori Takayama, Hampus Hammarlund

Statistical analysis: Takumi Meguro, Fuminori Takayama

Interpretation of results: Takumi Meguro, Fuminori Takayama, Masaru Honjo

References: Takumi Meguro, Fuminori Takayama

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