Smartphone-based digital peer support for a walking intervention among public officers in Kanagawa prefecture: Single-arm pre-and post-intervention

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Abstract

Background: Digital peer support, defined as peer support delivered through technology and media, such as smartphone apps, may be promising for step-count promotion. Interactions among users had a positive impact on the retention rate, and apps with social elements showed significant improvements in daily step counts. However, the feasibility of digital peer support in promoting physical activity (PA) is unknown; therefore, its effectiveness on step counts and its clinical implications remains unconfirmed.

Objective: This study used retention rate and evaluated its feasibility during a three-month intervention period. Changes in daily step counts were reviewed, and the association between the achievement of daily step goals and increased daily step counts was examined. Changes in physical measurements, lifestyle characteristics, and psychosocial factors were compared before and after the intervention.
The study design was a 3-month one-arm intervention with participants from local government offices in Kanagawa, Japan. We used an available and accessible smartphone app, Minchalle, as the tool for the group intervention.

Methods: The study design was a 3-month one-arm intervention with participants from local government offices in Kanagawa, Japan. We used an available and accessible smartphone app, Minchalle, as the tool for the group intervention.

Results: Of the 63 participants who enrolled, 62 completed the intervention. The retention rate was 98% (62/63). The average daily step count during the intervention was 6,993 (standard deviation (SD):2,328), a 1,182-step increase compared to that observed one week before the intervention began. The achievement rate of daily step counts during the intervention was 53.5% (SD: 26.2). There was a significant correlation (r=0.27, P=.05) between achieving and increasing the daily step count. Comparative analyses showed that changes in weight, body mass index (BMI), somatic fat rate, systolic blood pressure (sBP), and diastolic blood pressure (dBP) were significantly different before and after the intervention (weight: 68.56 kg (SD: 16.97) vs 67.30 kg (SD: 16.86), P<.01, BMI: 24.82 kg/m2 (SD: 4.80) vs 24.35 kg/m2 (SD: 4.73), P<.01, Somatic fat rate: 28.50% (SD: 4.84) vs 26.58% (SD: 7.90), P<01, sBP: 130.42 mmHg (SD: 17.92) vs 122.00 mmHg (SD: 15.06), P<.01, and dBP: 83.24 mmHg (SD: 13.27) vs 77.92 mmHg (SD: 11.71), P<.01, respectively). Similarly, daily amount of PA significantly improved from 5.77 metabolic equivalents (METs) hour per day (SD: 3.81) to 9.85 METs-hour/day (SD: 7.84), P<.01. However, no significant differences were observed in lifestyle characteristics or psychosocial factors.

Conclusions: This study demonstrated that digital peer support proved feasible for maintaining high retention rate and can, therefore, effectively promote PA. It can be a promising tool for improving daily step counts, subjective PA, and clinical outcomes, such as weight, BMI, somatic fat rate, and blood pressure. Clinical Trial: UMIN Clinical Trials Registry: UMIN000042520

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Introduction

Interventions for health promotion and behavioral changes using smartphone apps may be more cost-effective than face-to-face services due to their affordability and accessibility. The usefulness of smartphone apps in increasing physical activity (PA), including step count, is evident. Previous studies have reported that smartphone app interventions had a positive impact on both objective and subjective PA [1-4], including walking time [5, 6].

Peer support refers to the process through which individuals who share common experiences or face similar challenges come together as equals to offer and receive help based on the knowledge that comes through shared experiences [7]. This includes psychological support such as acceptance and encouragement. To date, face-to-face peer support has been effective in increasing PA, including step count, in the general population without illness [8]. Conversely, peer support also poses challenges for in-person style owing to the high travel costs, organization, and human resources required.

In contrast, smartphone apps are inexpensive and accessible, making it possible to provide services to a multitude of people at a lower cost than face-to-face meetings. To overcome the challenges of conventional peer support, digital peer support—defined as peer support delivered through technology and media, such as smartphone apps [9]—has been recently developed. Previous studies have indicated that communication with peers and social support [10] may have a positive impact on increasing step count [11]. Therefore, digital peer support may be promising for step-count promotion.

To date, the feasibility or engagement of digital peer support is unclear, although the usage of smartphones is related to the magnitude of their effects [4, 12]. Most previous studies defined engagement as the retention rate, by calculating the percentage of users who continued using smartphone apps during the intervention [13]. However, there is no consensus on measuring engagement; attempts have been made for conceptualization [14-16]. In general, the retention rates of healthcare smartphone apps for physical activity are low at approximately 45% [17], and usage of smartphone apps has declined over time [1, 18].

Social features of smartphone apps, such as social support and social comparison through interactions among users, reportedly have a positive impact on engagement, and they are considered a potential leverage to increase the retention rate [18-20]. However, no studies have verified the retention rate of specialized digital peer support, and therefore, its effectiveness on step count remains unconfirmed. In a single-armed pre-post comparison study that examined the efficacy of smartphone apps, where social networking was the main component, the retention rate among 55 participants was 82% during a six-month-long intervention [21]. Another two intervention arms (gamification and basic apps) from a three-group randomized control trial (RCT) for 100 days evaluated the efficacy of a smartphone app equipped with gamification, including social interaction among users, on promoting PA [12]. In that study, attrition (30 days of nonuse) was reported in approximately 32% and 39% of the gamified and basic app groups, respectively, meaning the retention rates of both groups were 68% and 61% [16]. Moreover, the gamified app group demonstrated significantly increased subjective PA at the nine-month follow-up compared to the control group that engaged in individual walking. However, the effect on objective step counts was not revealed [22].

We aimed to assess the effectiveness of digital peer support as a tool for promoting health. This study evaluated the feasibility of digital peer support over a three-month intervention period via retention rates. We also measured its effectiveness. Specifically, pre- and post-intervention comparisons were made regarding changes in physical measurements, PA, lifestyle characteristics, and psychosocial factors. Additionally, previous studies revealed that goal setting and self-monitoring contributed to increasing step counts [4, 23, 24]. Hence, this study also examined the relationship between the goal attainment rate and increasing step counts using digital peer support. If its effectiveness were demonstrated, it would help individuals increase step counts easily, at a low cost, and remotely. Furthermore, digital peer support may be used as an intervention tool during medical consultation intervals for patients with lifestyle-related diseases or others for whom walking is effective for disease prevention or control.

Methods

Study Design and Procedures

This three-month, one-arm intervention study adopted a pre-post evaluation design. Baseline assessments, which consisted of paper-based questionnaires and physical measurements, were conducted in gymnasiums and other facilities arranged by the seven municipalities in Kanagawa Prefecture and Kanagawa local government offices that participated in the study. The measurements were taken by the researchers or local municipal officials in Kanagawa Prefecture and Kanagawa local government officials trained by the researchers. Subsequently, the participants installed and set up a smartphone application called Minchalle ("Challenge yourself together with others," in Japanese) to commence the intervention.

Participants were required to send objective step count data for one week before the intervention as a baseline and data during the intervention period at three months via Minchalle. Objective step count data were measured using Google Fit (*Google LLC,* California, U.S.A.) for Android users and Healthcare for iPhone users (*Apple, Inc.*, California, U.S.A.), both capable of automatically counting steps while the phone was carried. Once Minchalle was connected to these apps, daily step count data were automatically transferred to and displayed in Minchalle. Following the three-month intervention, participants were again required to complete paper-based questionnaires and undergo physical measurements as part of an endline survey. Endline measurements were performed in the same manner as the baseline assessments. In addition, to assess the validity of smartphone-measured data, a one-week step-count measurement via an accelerometer (Active style Pro HJA-750C; developed by *OMRON Corporation*, Osaka, Japan) was conducted before the intervention. Participants were required to wear the accelerometer around their waist while awake during this period. The study was conducted between December 2020 and June 2021.

Recruitment and Participants

This study was announced through email or online in the offices of seven local municipalities in Kanagawa Prefecture and Kanagawa local government offices in Japan. Interested participants participated in briefing sessions to deepen their understanding of this study, and, if eligible, paper-based informed consent was obtained. Inclusion criteria were participants aged between 20 and 75 years who owned and were accustomed to using a smartphone and could communicate in Japanese. Exclusion criteria were participants who were currently pregnant, had physical or medical problems that did not allow safe participation in the walking intervention, had experience using Minchalle over the past six months, or had undergone another face-to-face or digital interventional study for PA promotion. The recruitment was conducted between December 2020 and April 2021.

Intervention

Minchalle was commercially developed by a healthcare company (*A 10 Lab*, Tokyo, Japan) to help users foster desirable habits. It is available on both Android and iPhone. Its development was guided by the Social-Cognitive Theory (SCT), based on the need to increase self-efficacy, a key driver of behavior adoption and maintenance. To enhance self-efficacy, Minchalle adopted a group intervention to maximize the mechanisms of social support and comparison among group members, which thereby increased the retention rate and made substantial achievements. Based on this basic concept, the main function of Minchalle was to facilitate group interactions, limiting each group to a maximum of five members and a minimum of three members with similar goals. All users were required to share their daily achievements with other members in a chat box, accompanied by a photo taken on the same day as evidence of their activity. Users could also enjoy interactions with other members by commenting or chatting at any time, although this was not obligatory. This platform was designed to help users continue desired behaviors by receiving praise and encouragement from other members for their achievements and gaining inspiration from other members' activities. Apart from group interaction, the examples of functions installed in Minchalle were goal setting, self-monitoring, reminders through push notifications, rewards for achievements such as exclusive stickers available within this app, and coins that could be used for donations to organizations that implement projects with social significance.

In this study, once the Minchalle app was installed, participants were anonymously assigned to a group that consisted of a maximum of five members by researchers. Each participant set their daily step goals based on their step counts from the past few days, without any instruction from the researchers. The intervention began with participants posting a photo of their total step count once a day in the group chat. To easily identify study participants, all the team members were composed exclusively of study participants. For their cooperation, participants were provided access to a premium version of Minchalle by A 10 Lab worth 500 JPY during the intervention period.

Sample size

In a similar pilot study in Australia measuring the effectiveness of a social networking mobile app on improving physical activity, the number of participants was 55. Therefore, we set a target of approximately 50 participants.

Measures

This study aimed to evaluate the feasibility of digital peer support interventions using retention rates. The secondary endpoints were the effectiveness of the intervention, measured via the changes in step counts between the baseline and endline, and the association with the achievement rate of daily step goals.

Retention rate

In this study, the retention rate was defined as the percentage of users who continued using smartphone apps during the three-month intervention period. This indicator was used based on its common usage in previous studies [13]. Owing to the setting up of Minchalle, participants were automatically removed from peer groups if they failed to report daily step counts or share any photos or comments for eight consecutive days. Therefore, participants who were dismissed but returned to the team were counted as participants, and only participants who were dismissed and never returned were considered as having dropped out.

Daily step counts

Objective daily step count data were obtained from Google Fit for Android users and HealthKit for iPhone users. All participants were required to submit their step data via Minchalle at both baseline and endline. The validity of Google Fit and Healthcare was confirmed, although interpretation should be done cautiously owing to the possibility of an underestimation of 10–20% due to non-carrying time [25-27]. Participants were asked to carry their smartphones for as long as possible while they were awake, live their daily lives, and report all the data at the end of the survey via the smartphone app. In this study, the positive impact on daily step counts was examined by comparing the average daily step counts during the week before and during the intervention. To calculate the average daily step count, the total daily step count was divided by the number of intervention days. Days with 0 counts were omitted to prevent underestimation, as there was a possibility that participants had forgotten to carry their smartphones that day. Moreover, the analysis included days with low step counts, as it was difficult to distinguish whether it reflected a step count issue or genuinely low PA.

Achievement Rate of Daily Step Goals

At the beginning of the intervention, participants were asked to set their daily step goals based on their step counts from the past few days, without any instructions from the researchers. These goals could be adjusted by the participants at any time during the study. The achievement rate was assessed by calculating the proportion of days on which participants met their daily step goal relative to the total number of intervention days.

Other Measurements

This study used a self-administered questionnaire to obtain sociodemographic characteristics, which included sleep, subjective PA, alcohol consumption, smoking, diet, personality and psychological traits, psychological stress, social relationships, quality of life (QOL), and physical checkups. These questionnaires were used in the Kanagawa ME-BYO prospective cohort study, a large population-based genomic cohort study to clarify gene–environmental interactions in non-communicable diseases (NCDs) in collaboration with the J-MICC Study [28]. Details of the ME-BYO cohort and J-MICC study and the relationship between the two have been described elsewhere [28-30]. Questionnaires on loneliness and self-efficacy were also used in this study.
Height and weight were measured to the nearest 0.1 cm and 0.1 kg, respectively, and body mass index (BMI) was calculated. Systolic and diastolic blood pressure (sBP and dBP, respectively) were measured via anthropometry. Lifestyle factors included subjective PA, smoking habits, alcohol consumption, and sleep hours per day. We defined subjective PA as the sum of the daily amount of PA, estimated by multiplying the

amount of time spent walking (3.0 metabolic equivalents (METs)) and engaging in hard labor (4.5 METs) and their assigned daily amounts of MET intensities, and three types of leisure-time activities (3.3 METs for light effort, 4.0 METs for moderate effort, and 8.0 METs for vigorous effort), calculated by multiplying the daily frequency, duration, and intensity. We also assessed the METs for engaging in hard labor (4.5 METs) alone. Detailed information on the calculation method has been provided in previous studies [31-33].

The Kessler Psychological Distress Scale (K6) is a six-item screening scale with a 5-point rating that evaluates psychological distress in the preceding month. Higher scores indicate higher levels of psychological distress. Its validity and reliability have been described previously [34]. Social support items were derived from the ENRICHD Social Support Inventory (ESSI) [35]. The original version of the ESSI includes seven items measured with a 5-point rating to assess the four domains of social support: emotion, instrument, information, and appraisal. Individual items are summed for a total score, with higher scores demonstrating greater social support. This study adopted a modified version of the ESSI that included six items to prevent duplication of the question on marital status. The Japanese version of the Short-Form Health Related Quality of Life (SF8) Health Survey was used to measure health-related quality of life. Details regarding this assessment have been previously described [36]. The Japanese version of the UCLA Loneliness Score was used, which consists of 20 items answered on a 4-point scale, with higher scores indicating a higher degree of loneliness [37, 38]. Self-efficacy was assessed using the Generalized Self-Efficacy Scale [39], which comprises 23 items rated on a 5-point scale to measure belief in one's competence to cope with a broad range of stressful or challenging demands [40]. Higher scores on this scale indicate a higher degree of self-efficacy.

Statistical Analyses

Descriptive analyses were conducted to calculate the retention and achievement rates of the daily step goals. The average daily step counts one week before and during the intervention period were calculated to measure the impact of the intervention, and the differences between the two were assessed. Pearson's coefficients were used to assess the correlation between the achievement rate of daily step goals and the difference in average step counts before and during the intervention. Differences in weight, BMI, somatic fat rate, sBP, dBP, PA, lifestyle characteristics, and psychosocial factors between baseline and endline were analyzed via a two-tailed t-test. Furthermore, Pearson's coefficients were examined between changes in average daily step counts and various variables, including physical measurements, lifestyle, and psychosocial factors, separately at the baseline and endline. This enabled us to determine the variables to be used for subsequent multi-regression analyses by omitting the possibility of multicollinearity among potential independent variables. Multiple regression analyses were conducted to demonstrate the impact of changes in daily step counts on health measurements, lifestyle, and psychosocial factors (Model 1), after adjusting for sex and age (Model 2), Model 2 + household income (Model 3), and Model 3 + average daily step counts during one week prior to the intervention (Model 4). Data analysis was performed using the R software (version 4.2.2).

Ethical Approval

This study was approved by the Institutional Review Board of Kanagawa University of Human Services (30-018). The study was registered in the UMIN Clinical Trials Registry (UMIN000042520). All the participants provided written informed consent. Data were collected in a face-to-face setting, and all user data were de-identified before analysis.

Results

Participants' Characteristics

Figure 1 shows the diagram chart of study participants. Table 1 presents the baseline characteristics of the 62 participants. Participants' ages ranged from 24 to 63 years, with a mean age of 43.6 (standard deviation (SD) 10.72) years. More than half were male (32/62, 51.6%), and most had a university degree or higher (45/62, 72.6%).

<Figure 1. Diagram chart of the study participants>

Table 1. Demographic characteristics of the 62 eligible participants	
	Number(%)
Age	
20-29	8 (12.9)
30-39	14 (22.6)
40-49	18 (29.0)
50-59	19 (30.6)
60-69	3 (4.8)
Sex	
Male	32 (51.6)
Female	30 (48.4)
Education	
High school	5 (8.1)
Vocational school	5 (8.1)
College	7 (11.3)
University	38 (61.3)
Graduate school	7 (11.3)
Job category	
Administrator	42 (67.7)
Manager	9 (14.5)
Technical staff	10 (16.1)
Others	1 (1.6)
Marital status	
Married	47 (75.8)
Single	14 (22.6)
Others	1 (1.6)

Retention Rate

Among the 69 participants who signed the consent forms, four withdrew shortly after the intervention began due to personal conditions or smartphone defects, two did not meet the eligibility criteria, and one dropped out in the middle. Therefore, the number of participants who installed the application and started the intervention was 63, with a retention rate was 98% (62/63).

Data on daily step counts were received from 54 (87%) of the 62 participants at the three-month endline. Eight participants failed to share the data on step counts at the endline due to misunderstanding the procedures of the survey when completing the intervention and endline questionnaires. Thus, data from 54 participants were used for step count analysis.

Improvement in Step Counts

The average daily step count during the week before the intervention began was 5,811 (SD 2,477), as measured by Healthcare for iPhone or Google Fit by Android, and 7,073 (SD 2,301), as measured by the accelerometer. Comparing the average daily step count by smartphone apps between baseline and during the intervention, a 1,182-step increase was observed. The change in average daily step counts according to sex, age, and BMI at baseline is shown in Supplemental Tables 1 and 2.

Achievement Rate of Daily Step Goals and Effect on Increase in Step Counts

The mean of the daily step goals at baseline was 6,808 (SD 1,668). The mean difference between the daily step goal and step count before the intervention began was 1,043 (p<.01). The achievement rate of the daily step count during the intervention was 53.5% (SD 26.2). A significant correlation (r=0.27, p=0.05) was observed between achieving daily step goals and an increase in daily step count. There was a statistically negative correlation between the difference in daily step goal and pre-intervention step count and an increase in daily step count ($r=-0.39$, $p<0.01$).

Other Outcomes

Table 2 and Supplemental Figure 1 show the comparative results of changes in health measurements, lifestyle characteristics, and psychosocial factors. Weight changes, BMI, somatic fat rate, sBP, and dBP were significantly different (weight: 68.56 kg (SD: 16.97) vs. 67.30 kg (SD: 16.86), $P<.01$, BMI: 24.82 kg/m^2 (SD: 4.80) vs. 24.35 kg/m^2 (SD: 4.73), $P<.01$, Somatic fat rate: 28.50% (SD: 4.84) vs. 26.58% (SD: 7.90), $P<.01$, sBP: 130.42 mmHg (SD: 17.92) vs. 122.00 mmHg (SD 15.06), $P<.01$, dBP: 83.24 mmHg (SD: 13.27) vs. 77.92 mmHg (SD: 11.71), $P<.01$). Similarly, the daily amount of PA was significantly improved from 5.77 METs-hour per day (SD 3.81) to 9.85 METs-hour per day (SD 7.84), ($P<.01$), and engaging in hard labor showed a similar trend ($P<.01$). However, no significant differences were observed in lifestyle characteristics or psychosocial factors. The results of the groupwise analyses between those with a maintained or increased step count and those with a decreased step count during the intervention are summarized in Supplemental Table 3.

Table 2. The difference in health measurements, lifestyle characteristics, and psychosocial factors between baseline and endline after 3-month intervention (N=62)

Objective variables		Baseline Variables*		Endline Variables*		p value
Weight (kg)		68.56	16.97	67.30	16.86	<.01
BMI (kg/m2)		24.82	4.80	24.35	4.73	<.01
Somatic fat rate		28.50	4.84	26.58	7.90	.01
sBP (□ Hg)		130.42	17.92	122.00	15.06	<.01
dBP (□ Hg)		83.24	13.27	77.92	11.71	<.01
Daily amount of PA (METs-hour per day)		5.77	3.81	9.85	7.84	<.01
Daily amont of engaging in hard labor (METs-hour per day)		1.31	1.80	3.59	6.08	<.01
Alcohol comsumption**						.17
	Yes (n)	33		24		
	No(n)	29		37		
Sleeping hours		6.04	0.95	6.09	0.97	.95
ESSI		23.66	5.37	22.84	5.65	.27
Physical function (Locomo 5)		0.90	1.72	0.75	1.68	.45
Depression and anxiety (K6)		4.52	5.00	4.58	5.34	.89
Psychological Stress***						.46
	High(n)	22		19		
	Moderate(n)	35		31		
	Low(n)	5		9		
	Not at all(n)	0		1		
Lonliness		41.97	8.92	42.61	10.46	.41
Self efficacy		69.98	11.47	70.56	13.33	.38
Health related QOL (EQ-5S)		0.91	0.10	0.89	0.15	.33

*Variables at both baseline and endline show Mean on the left and SD on the right row.

** Figures in the row of Variables show the number of each category and p-value of χ^2 analyses was shown in the column of p value. The number of total respondents was 61.

*** Figures in the row of Variables show the number of each category and p-value of trend test was shown in the column of p value. The number of total respondents was 60.

Table 3 demonstrates the correlation between changes in step count, health measurements, and lifestyle characteristics measured at baseline and endline. A significant difference was observed between weight and BMI (r=-0.41, *P*<.01 for both variables). The correlations between the changes in step count and psychosocial factors are shown in Supplemental Table 4. Table 4 shows the results of the linear regression analysis. The increment in step counts was significantly associated with weight, BMI, and sBP, even after adjusting for sex and age (Model 2, *P*=.02 for weight and BMI, *P*<.01 for sBP), household income (Model 3, *P*=.04, *P*=.03, *P*=.01, respectively), and all the covariates (Model 4, *P*<.02 for weight and BMI, *P*=.01 for sBP). The results of the linear regression analysis to assess the association between changes in average daily step count and psychosocial factors are summarized in Supplemental Table 5.

Table 4. Linear regression of difference of physical measurement and lifestyle characteristics on average daily step counts at baseline and endline after 3-month intervention

Objective and explanatory variables***	Model 1 * (N=53) Regression coefficient$	p value	Model 2** (N=53) Regression coefficient$	p value	Model 3** (N=46) Regression coefficient$	p value	Model 4** (N=46) Regression coefficient$	p value
Weight (kg)		<.01		.02		.04		.02
Change in step count	-0.4006		-0.4152	<.01	-0.3399	.01	-0.4776	<.01
Sex			-0.1370	.81	-0.3544	.54	-0.7247	.22
Age			0.0176	[illegible]	[illegible]	[illegible]	[illegible]	.85
Household income					-0.8663	.17	-0.0014	.12
Step count at baseline							-0.0002	[illegible]
BMI (kg/m2)		<.01		.02		.03		.02
Change in step count	-0.1467		-0.1510	<.01	-0.1253	.02	-0.1695	<.01
Sex			-0.1294	.53	-0.2662	[illegible]	-0.3409	.13
Age			0.0062	.53	-0.0061	.62	-0.0030	.80
Household income					0.0005	[illegible]	0.0005	.11
Step count at baseline							0.0005	.11
Somatic fat rate (%)#		.31		.45		[illegible]		.35
Change in step count	[illegible]		-0.2006	.42	0.0015	[illegible]	-0.1399	.66
Sex			-0.1791	.87	-1.2000	.32	-1.4732	.24
Age			[illegible]	.22	-0.1247	.07	-0.1135	.10
Household income					0.0013	[illegible]	0.0012	.50
Step count at baseline							-0.0003	.33
sBP (□ Hg) ##		.06		**<.01**		**.01**		**.01**
Change in step count	-1.9820		-1.8190	.07	-2.0350	.09	-2.9610	.03
Sex			11.7100	<.01	13.7358	.01	11.9093	.02
Age			-0.3203	.13	-0.0904	.75	-0.0361	.90
Household income					-0.0904	.12	-0.0122	.12
Step count at baseline							-0.0018	.13
dBP (□ Hg) ##		.91		.33		.42		.57
Change in step count	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	.78
Sex			6.7060	.07	7.6480	.06	7.8010	.07
Age			0.0461	.79	0.0471	.83	0.0426	.83
Household income					[illegible]	[illegible]	[illegible]	.90
Step count at baseline							0.0002	.87
Daily amount of PA (METs-hour per day)		.45		.09		.22		.21
Change in step count	-0.3979		-0.1993	.69	-0.3899	.51	-0.0133	.98
Sex			-4.1360	.07	-3.1282	.22	-2.4910	.34
Age			-4.1360	.12	-0.0524	.71	-0.0784	.58
Household income					-0.0049	.21	-0.0048	.22
Step count at baseline							0.0007	.24
Daily amont of engaging in hard labor (MET- hour per day)		.28		.02		.10		.17
Change in step count	-0.4305		-0.2576	.49	-0.2591	.56	-0.1970	.70
Sex			-3.6871	.03	-3.3468	.08	-3.2419	.10
Age			-0.1460	.07	-0.0953	.36	-0.0996	.35
Household income					-0.0953	.34	-0.0027	.35
Step count at baseline							0.0001	.80
Alcohol consumption ###		.30		.23		.28		.37
Change in step count	-0.0694		-0.0621	.35	-0.0784	.26	-0.1015	.20
Sex			0.1476	.43	0.1242	.51	0.0985	.62
Age			-0.0139	.12	-0.0139	.12	-0.0125	.18
Household income					-0.4438	.38	-0.4183	.41
Step count at baseline							<-0.0001	.52
Sleeping hour #		.31		.30		.17		.22
Change in step count	0.0557		0.0460	.41	0.1246	.04	0.0995	.15
Sex			0.2990	.12	0.0906	.65	0.0658	.75
Age			-0.0053	.57	0.0906	.29	-0.0104	.35
Household income					-0.0001	.73	-0.0001	.75
Step count at baseline							<-0.0001	.43

*Model 1 shows simple regression analysis result.

**Model 2, 3, and 4 demonstrates the results of multi-regression analyses adjusting for sex and age(Model 2), sex, age and household income(Model 3), and all covariates(sex, age, household income and step count at baseline)(Model 4) respectively.

***Bold letter shows objective variables while normal font represents explanatory variables.

The figure of respondents was 51 in Model 1, 51 in Model 2, 44 in Model 3, and 44 in Model 4.

##The figure of respondents was 52 in Model 1, 52 in Model 2, 45 in Model 3, and 45 in Model 4.

The explanatory variable was dichotomous; drinking alcohol at both baseline and endline, or drinking only at baseline but quit it at endline

$ Regression coefficient shows the amount of changes of each objective variable by 1000 steps

Table 3. Pearson's coefficients between change in average daily step counts and difference in physical measurements and lifestyle characteristics between baseline and endline (N=54)

Objective variables	Correlation coefficient	p value
Weight (kg)	-0.41	<.01
BMI (kg/m2)	-0.41	<.01
somatic fat rate (%)*	-0.15	.31
sBP (□ Hg)*	-0.26	.06
dBP (□ Hg)*	-0.02	.90
Daily amount of PA (METs-hour per day)	-0.11	.45
Daily amont of engaging in hard labor (METs-hour per day)	-0.15	.27
Alcohol consumption*	NA**	.13
Sleeping hours*	0.14	.31

The exact intervention period varied from participant to participant. The days of the intervention period and the number of participants concerned are as follows: 90 days for 11, 92 days for 10, 93 days for 5, 94 days for 13, 98 days for 6, 99 days for 2, and 101 days for 7.

*Number of respondents were 51 for somatic fat rate and sleeping hours and 52 for sBP and dBP, and alcohol consumption.

**Trend test (jonckheere.test) was conducted and NA indicated not applicable.

Discussion

This study demonstrated the feasibility, as indicated by the retention rate, of digital peer support. The finding that 98% of all the participants continued to use the smartphone app even after the three-month intervention shows that the retention rate in this study was higher than that of any other smartphone app equipped with the function of group interaction for promoting PA. A meta-analysis reported that engagement was generally low, while the retention rate of online social networks varied depending on the number of participants and the duration of the intervention [41]. A systematic review that examined the impact of social networks reported retention rates ranging from 60% to 80% [42]. An RCT assessing the efficacy of a smartphone app that facilitates interaction among users regarding walking over a 100-day intervention period reported that retention rates in the 60% percentile were higher compared to those in previous studies [16]. In a similar study evaluating a single-arm intervention for six months targeted at university students, in which user interaction was one of the components, the retention rate was 82% [21]. Considering these figures, digital peer support was effective in maintaining a high retention rate and can, therefore, be a promising tool for affordable and accessible health promotion. A reason may be that daily interaction, which included social support and competition among participants and mutual comparison, served as a positive factor for the prolonged usage of smartphone apps, as shown in previous studies [18]. Another reason may be that the intervention period of this study was relatively short. Previous research has pointed out that the retention rate of smartphone apps generally remains high in short-term interventions from a few weeks to several months but tends to decrease after approximately six months from the beginning of the intervention [3]. We have conducted an RCT with a six-month intervention period (UMIN000046936) to assess the effectiveness of digital peer support, including its long-term effects.

This study also showed that digital peer support had the potential to increase PA. Participants' daily average step counts (+1,182 steps), subjective daily amount of PA (+4.08 METs), and daily amount of engagement in hard labor (at +2.28 METs) increased during the intervention period compared to one week before the intervention. Although step counts were lower than those in a meta-analysis [4], which showed that an average 13-week intervention increased the number of steps per day by 1,850, these results were consistent with those of other studies that showed increased objective PA [3, 6]. The high retention rate in this study may have led to a significant increase in the amount of PA. These results indicated that digital peer support improved PA and daily step counts. Additionally, this study demonstrated that the percentage of goal attainment was 53.5% (SD 26.2). Furthermore, the statistical correlation between the achievement rate of daily step goals and the amount of increase in daily step counts showed a significant difference ($r= 0.27$, $P=.05$), which was consistent with a previous study that reported that self-regulating, such as goal setting and self-monitoring, was a factor that influenced an increase in step counts. Apart from self-regulation, previous studies revealed that other behavior change techniques, such as feedback, were also effective in improving PA [43]. Therefore, future studies should examine the impact of other behavior-change techniques on digital peer support.

This study also suggested that digital peer support had the potential to improve health outcomes. Pre- and post-intervention comparisons showed reduced weight (-1.26 kg), BMI (-0.47 kg/m^2), somatic fat rate (-1.92%), sBP (-8.42 mmHg), and dBPe (-5.32 mmHg). These results were consistent with meta-analyses that examined the effectiveness of individually engaged smartphone apps on health outcomes [44]. Weight, BMI, and sBP could have decreased owing to the increased step counts that resulted from the smartphone app use. Participants' mean age in this study was 43.8 years, which was similar to that in a previous study that found significant weight loss in participants with a mean age of 45 years or higher [6]. However, it remains unclear in which age group digital peer support is particularly effective for promoting health outcomes. Changes in health outcomes are currently being investigated in our ongoing RCT (UMIN000046936), which will also examine which demographic backgrounds are likely to improve health outcomes.

Limitations and Future Direction

This study demonstrated the possibility that digital peer support played an important role in increasing step counts and thereby improving health outcomes with a high retention rate. However, several challenges remain unaddressed. First, it was a single-arm intervention. Since this study used a before-and-after comparison, other factors that may have affected step counts and health outcomes could not be excluded. Furthermore, the effectiveness could not be verified in detail. Therefore, we are currently conducting an RCT

(UMIN000046936). Second, the daily step counts measured by smartphone apps may be underestimated compared to their true value. Our findings revealed a difference of approximately 18% in daily step count during the week before the intervention between smartphone apps (5,811) and accelerometers (7,073). This finding was consistent with those of previous studies that found that the number of step counts measured by smartphones was 12–20% lower than the true value owing to where on the body the phone was being carried or intermittent bouts of activity [25, 26]. Therefore, our results of daily step counts during the intervention should be interpreted based on these limitations. Third, a previous study reported that the retention rate of applications with social features is related to personal preferences. For example, users' intent to use smartphone apps and a positive attitude toward technology, which were influenced by the simplicity or user-friendliness of the apps, were identified as positive factors for engagement [45, 46]. The stage of behavioral change also affected the continued use of apps [18]. As this study did not collect information on personal preferences, future research should examine the effects of personal traits on the continued use of digital peer support. Fourth, the study did not elucidate participants' specific backgrounds and lifestyles, examples of which were age, BMI [16], and being less physically inactive [21]. Although there was a slight increase in daily step counts among middle-aged or older individuals or those who were overweight before the intervention, these were not statistically significant. However, future research is required to verify the groups or demographics more likely to increase step counts using digital peer support. Fifth, the intervention of this study was conducted between the winter and spring seasons, and the impact of seasonality on PA was not considered, while previous research demonstrated PA level variations across the seasons, with a higher PA level in the summer compared with other seasons [47]. The possibility of seasonal and environmental effects should be considered when designing interventions in future research. Finally, the number of participants in this study was 69, which might have been underpowered to measure changes in health outcomes. The sample size was not calculated in this study because there were no prior studies examining the effectiveness of digital peer support on health outcomes. Future studies are needed to assess its effectiveness on both step counts and health outcomes, so that effect sizes can be calculated appropriately.

Conclusion

This study demonstrates that digital peer support is feasible for maintaining high retention rates and can, therefore, effectively promote PA. Digital peer support can be a promising tool from a clinical perspective for improving daily step counts, subjective PA, and health outcomes, such as weight, BMI, somatic fat rate, and blood pressure.

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Conflicts of Interest

The authors declare that this study was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Abbreviations

METs: metabolic equivalents
PA: physical activity
RCT: randomized controlled trial
SD: Standard deviation

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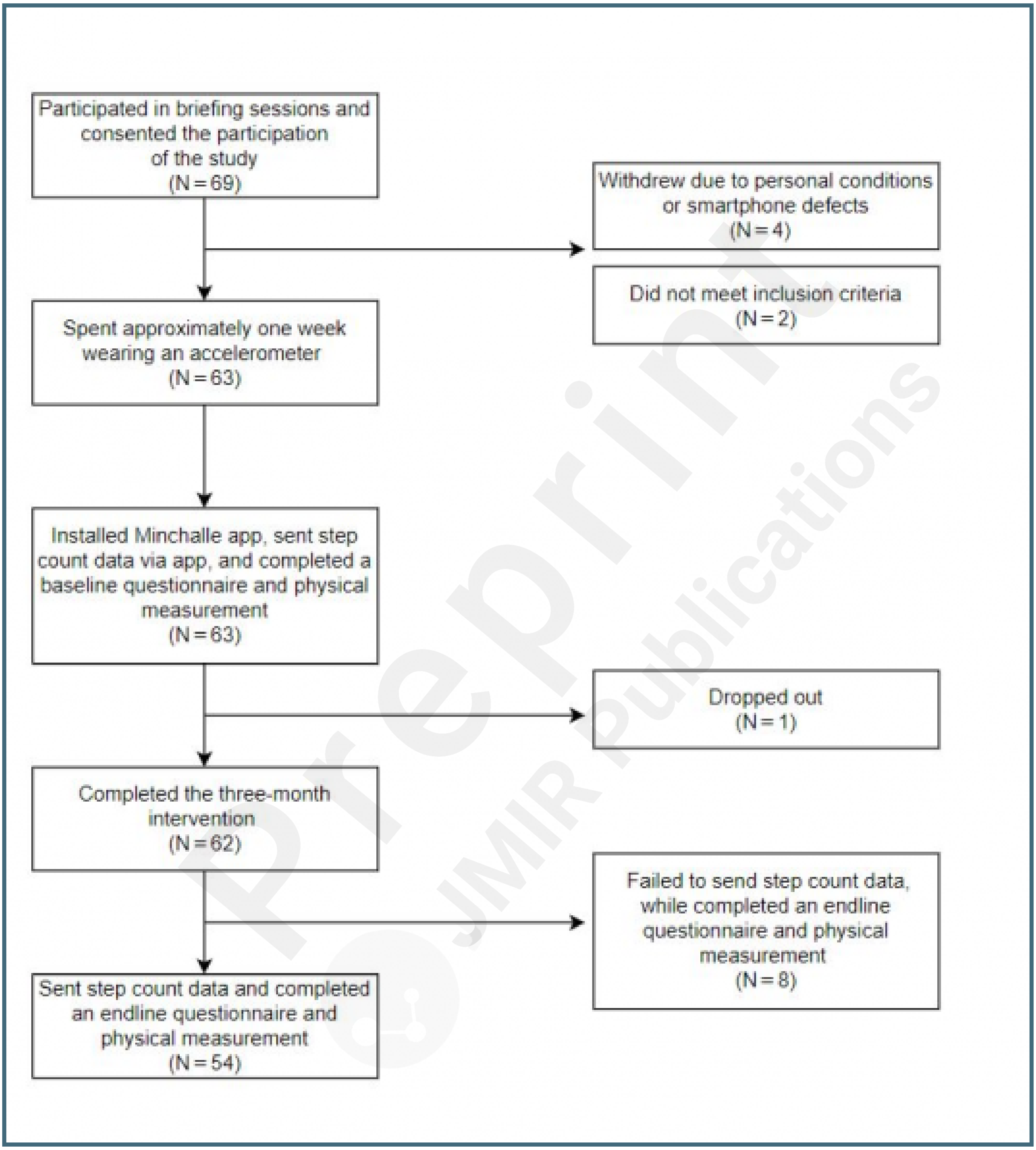
Supplementary Files

Figures

This is newly added in the Results section following the comments from the reviewer.



Multimedia Appendixes

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