J. Phys. Ther. Sci. 36: 647–655, 2024

The Journal of Physical Therapy Science

Original Article

Impact of tailored message notifications for frailty prevention in older adults: a quasi-randomized controlled study using a regression discontinuity design

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Abstract. [Purpose] This study investigated the potential of tailored message notifications based on municipal health check-up results to improve pre-frailty and frailty in older adults. [Participants and Methods] This study was conducted in Iiyama City, Nagano Prefecture, Japan, by using the Kihon Checklist to assess the health status of older adults. Since 2019, Iiyama City has sent notifications to individuals with pre-frailty (Kihon Checklist score: 4–7) and frailty (Kihon Checklist score: ≥8). A regression discontinuity design was used to estimate the effects of the intervention by comparing the groups with scores just above and below the cutoff points. Data from 6,382 individuals aged ≥65 years from 2019 to 2022 were analyzed. [Results] The intervention slightly improved the Kihon Checklist scores in the pre-frailty group. No statistically significant effects were observed in the frailty group or after multiple imputations for missing data. [Conclusion] The findings suggest that tailored message notifications can improve frailty prevention among pre-frail older adults. However, the limited frequency and content of these messages may have reduced their effectiveness. Therefore, more frequent and targeted messages are needed to address the needs of frail individuals.

Key words: Frailty, Kihon Checklist, Regression discontinuity design

(This article was submitted Jun. 14, 2024, and was accepted Jul. 16, 2024)

INTRODUCTION

Modern society is facing a rapid increase in the aging population, making the well-being and health maintenance of older adults an urgent issue. As of 2023, the proportion of people aged 65 years and older in Japan will reach approximately 30%, and is expected to continue to increase[1)]. Frailty presents significant challenges for older adults. The condition involves a decline in physical and cognitive abilities due to aging and is a reversible state between a healthy state and one requiring care. Early detection and proactive intervention can prevent or ameliorate the progression of frailty[2)]. At the community level, efforts to prevent frailty include both direct and indirect approaches. Direct approaches include offering health promotion classes, while indirect approaches include distributing leaflets and increasing awareness. Health promotion classes are practical because they address individual problems through direct intervention; however, challenges include difficulty in operation and low participation rates[3, 4)]. Conversely, distributing leaflets and raising awareness are simple and economical methods that broadly approach the community. However, there is inconsistent evidence regarding their effectiveness in knowledge impartation and behavioral change[5)].

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In this context, approaches offering personalized advice while appealing to large groups have been pursued. Recently, mHealth, which uses information and communication technologies, has gained attention. mHealth refers to efforts to provide and support health information and medical services using mobile devices (such as mobile phones, personal digital assistants, and other wireless devices)[6]. It is primarily used in resource-limited environments to improve healthcare delivery, support healthcare professionals, and enhance patients' self-management abilities. Tailored text messages and mHealth interventions are promising methods for maintaining the health of older adults[7]. These simple and economical methods enable effective dissemination of information to older adults. Interventions using text message transmission via mobile phones have been reported to improve health behaviors among older adults[8]. However, these effects are limited to simple outcomes, such as improving physical activity, nutrition, and medication adherence. There are no consistent conclusions regarding the impact of mHealth interventions on complex outcomes, such as instrumental activities of daily living. Furthermore, the introduction of mHealth for older people faces barriers in terms of, for example, device usage literacy and equipment setup[9]. Thus, the spread of such technologies remains challenging in mountainous regions.

Individuals in regions with geographical barriers and those with limited device usage literacy primarily receive alerts in the form of letters and health guidance from municipalities. In this context, our challenge is to devise simple and somewhat tailored interventions that can be effectively implemented in this population. Therefore, in this study, we aimed to address this challenge by investigating the potential of sending alerts through tailored messages based on the results of municipal health checks to prevent frailty and pre-frailty among older adults.

PARTICIPANTS AND METHODS

This article describes efforts to prevent frailty in Iiyama City, located in a mountainous region of Nagano Prefecture, Japan, with a considerable aging population. The study used data provided by Iiyama City and was obtained using an opt-out approach in terms of consent. The study was approved by the Ethics Committee of Shinshu University (trial number 6127).

Since 2010, Iiyama City has conducted annual comprehensive surveys using the Kihon Checklist (KCL) to assess the health status of older adults. The surveys target all healthy older individuals aged 65 years and over. The district staff collect the questionnaires directly from the individuals and send them to Iiyama City.

This retrospective observational study used data from 2019 to 2022, and the corresponding data from the previous and subsequent years were compared. The survey response rate was 89%, with 16,221 respondents (5,342 in 2019, 5,439 in 2020, and 5,440 in 2021). Those who received long-term care insurance certification, moved residence, or died during the survey period were excluded from the study. Duplicate data from individuals who received messages multiple times were excluded, and data from the first year of receiving messages were used. As a result, the data of 6,382 individuals were analyzed (Fig. 1).

The collected demographic variables included age, sex, and body mass index (BMI). Additionally, the Kihon Checklist (KCL) was used to assess frailty. The KCL is a self-reported yes/no survey consisting of 25 items. It is widely used to identify older adults at risk of requiring care or assistance in the near future due to physical, mental, and social functions in daily life[10]. The KCL score was correlated with the number of frailty phenotypes according to the frailty index criteria of the Cardiovascular Health Study. Recently, it has also been used for frailty screening[11, 12]. Using the KCL score, individuals

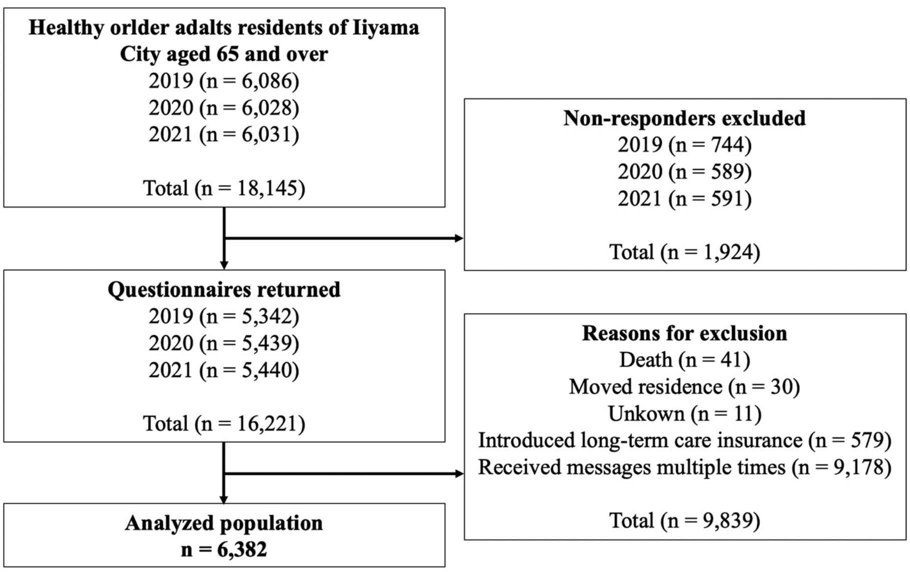

Fig. 1. Process for selecting analyzed population

with 0–3 points were considered robust with no health issues; those with 4–7 points, at a high risk of pre-frailty; and those with 8 points or more, frail. From the 2019 survey, Iiyama City sent message notifications to individuals with KCL scores of 4–7 (pre-frailty) and 8 or higher (frailty) to alert and educate them about frailty prevention. The frequency of messages is once per year. When the total score exceeded the cutoff value, advice was offered on exercise and diet to prevent pre-frailty and frailty and guidance was provided to create a fulfilling life. Additionally, for those with problems in the KCL sub-items, advice was provided for each corresponding item (Table 1).

If groups with and without intervention can be separated by a certain threshold, the intervention effect can be estimated using a regression discontinuity design (RDD). It is a form of quasi-randomized controlled trial that estimates the causal effects of interventions using a cutoff point. In this design, interventions are applied only to individuals who exceed a certain threshold, whereas those below are treated as the control group. Accordingly, we used an RDD[13)], in which participants with pre-frailty and frailty based on their baseline KCL scores were selected as the intervention group if they exceeded the relevant cutoff points, and those below these points were selected as the non-intervention group.

The core of the RDD is based on the assumption that participants around the cutoff point have similar background factors, allowing for a more accurate grasp of the intervention's effects by comparing data only near the cutoff point. Local regression analysis was used near the cutoff point, formally employing the model $Y=\beta 0+\beta 1(X-c)+\epsilon$, where Y is the outcome variable, X is the independent variable, and ϵ is the error term. The dependent variable in this study was the KCL score after 1 year, with the baseline KCL score used as the independent variable. Despite a high questionnaire response rate, some KCL data were incomplete; therefore, missing values were imputed using multiple imputations (MI) with the expectation-maximization bootstrapping algorithm[14)]. The number of imputations was set to 100 (M=100)[15)]. A sharp RDD was applied, because message notifications were sent only to those above the cutoff point[16)]. We also performed sensitivity analyses at different bandwidths to test the consistency and robustness of the estimated effects.

Table 1. Message alerts to participants in the pre-frailty and frailty groups

Overall guidance
What is frailty?
Frailty is the state of being "slightly weakened (frail)," between healthy and in need of care. If you have frailty, it is possible to return to a healthy state, depending on your measures.
How is frailty determined?
It is based on the total score of items 1–25 on the Kihon Checklist.
Your total Kihon Checklist score is ** points
Your state is **. (Robust or Pre-frailty or Frailty here)
How to prevent frailty
Exercise, a well-balanced diet, interaction with neighbors and friends, and volunteer activities effectively prevent and improve frailty.
Guidance on reducing the score for each item
Items 1–5 asked about daily life
In this area, many "no" responses may indicate an inactive lifestyle. Review your daily life to increase the number of "yes" responses as much as possible.
Items 6–10 asked about motor function (condition of legs and feet)
You may have muscle weakness if any of these items apply to you. If muscle strength declines, you may become inactive in all aspects of life or bedridden due to falls, etc.
Items 11 and 12 asked about nutritional status
Neither being too thin nor too fat is good for your health. Make sure you have a well-balanced diet.
Items 13–15 asked about oral health status
If any of these items apply to you, you may have decreased oral function (the ability to chew and swallow). Poor oral function can lead to malnutrition and pneumonia, worsening overall health.
Items 16 and 17 asked whether you are confined
If this applies to you, try going outside a little, such as to the garden on warm days, to change your mood.
Items 18–20 asked if you were concerned about memory loss
Many factors, including age, can cause memory loss, but if it interferes with social or family life, dementia may be a possibility. Prevention, early detection, and early treatment are important for dementia.
Items 20–25 asked if you feel depressed
If you answered yes, we are concerned about your mental fatigue. If you feel depressed or unmotivated, and your activity level declines, you may develop dementia or need long-term care. If you have any questions, please get in touch with us as soon as possible.

Statistical analyses were performed using R software (version 4.3.2; R Foundation for Statistical Computing, Vienna, Austria). For the RDD, we used the rdrobust package[17)], which is specifically tailored for robust nonparametric inferences in an RDD. This package facilitates the implementation of optimal bandwidth selection and bias-corrected confidence intervals, thereby ensuring the accuracy and reliability of the estimates. The Imbens and Kalyanaraman bandwidth[18)] was used for sharp RDD local regression. Bandwidth indicates the extent to which the scores were analyzed as a single group around the cutoff score. If the bandwidth is too wide, participants with different background factors may be included in the analysis. It is recommended to calculate the optimal bandwidth[13)]. The calculated bandwidth for the pre-frailty cutoff (KCL score=4) was 1.8; however, because it was too small for regression analysis, the smallest analyzable value of 2 was used. Therefore, the intervention effect on pre-frailty was calculated as the local average treatment effect (LATE) of the intervention group with KCL scores of 4–5 and the control group with KCL scores of 2–3. For the frailty cutoff, the KCL score was 8, and the calculated bandwidth was 5.2; however, to avoid including the robust group, the bandwidth was set to 4. The intervention effect on frailty was subsequently calculated as the LATE of the intervention group with KCL scores of 8–11 and that of the control group with scores of 4–7. Sensitivity analyses were conducted at different bandwidths for both the pre-frailty and frailty interventions[16)]. As a subgroup analysis, the effects were explored separately by age category (<75 years and >75 years), sex, and survey year (with baselines in 2019, 2020, and 2021).

Several assumptions must be met to implement an RDD[13)]. 1) Continuity of the baseline KCL score as a running variable. When the running variable is a scale to which individuals can respond and some gain is associated with exceeding the cutoff, an unnatural increase or decrease in numbers around the cutoff is observed. In Iiyama City, where the evaluation was conducted, there were no gains from exceeding the cutoff score, such as a discount on insurance premiums, making such a threat unlikely. As verification, the continuity of the local polynomial density estimator[19)] was assessed. The test results revealed p-values of 0.55 at the pre-frailty threshold and 0.51 at the frailty threshold, indicating continuity of the running variable. 2) The exchangeability of groups. The groups to be compared must have uniform background factors and other than the baseline KCL scores. However, differences in age and sex were observed between the groups, necessitating adjustment for these covariates in the RDD analysis (Tables 2 and 3).

The final regression specification designed to meet the RDD requirements is as follows:

$$Yi=\beta 0+\beta 1(Xi-c)+\beta 2\cdot \mathrm{I}(Xi\geq c)+\beta 3\mathrm{Age}i+\beta 4\mathrm{Sex}i+\epsilon i$$

where Yi is the outcome variable representing the follow-up KCL score for individual i. Xi is the running variable and the baseline KCL score centered on specific cutoff points: 4 for pre-frailty and 8 for frailty, where negative values indicate

Table 2. Demographic characteristics of the analyzed population for the pre-frailty threshold: comparison of message intervention vs. control groups (n=2,550)[a]

	Control group KCL score ≤3 (n=1,578)	Message intervention group KCL score ≥4 (n=972)	p-value	Overall (n=2,550)
Age, years	71.0 (67.0, 77.0)	73.0 (68.0, 80.0)	*	71.0 (67.0, 78.0)
Female, n (%)	831 (52.7)	504 (51.9)		1,335 (52.4)
Running variable				
Baseline KCL score	2.0 (2.0, 3.0)	4.0 (4.0, 5.0)	*	3.0 (2.0, 4.0)
Outcome				
Follow up KCL score	3.0 (1.0, 4.0)	4.0 (3.0, 6.0)	*	3.0 (2.0, 5.0)

[a]Bandwidth=2. n (%): Median (IQR). KCL: Kihon Checklist. *$p<0.05$ using the Wilcoxon signed-rank sum test or χ^2 test.

Table 3. Demographic characteristics of the analyzed population for the frailty threshold: comparison of message intervention vs. control groups (n=2,126)[a]

	Control group KCL ≤7 (n=1,527)	Message intervention group KCL score ≥8 (n=599)	p-value	Overall (n=2,126)
Age, years	74.0 (68.0, 81.0)	77.0 (70.0, 84.0)	*	75.0 (69.0, 82.0)
Female, n (%)	788 (51.6)	343 (57.2)	*	1,131 (53.2)
Running variable				
Baseline KCL score	5.0 (4.0, 6.0)	9.0 (8.0, 10.0)	*	6.0 (4.0, 8.0)
Outcome				
Follow up KCL score	5.0 (3.0, 7.0)	8.0 (6.0, 11.0)	*	6.0 (4.0, 8.0)

[a]Bandwidth=4. n (%): Median (IQR). KCL: Kihon Checklist. *$p<0.05$ using the Wilcoxon signed-rank sum test or χ^2 test.

scores below the cutoff. β1 captures the linear relationship between the baseline and follow-up KCL scores, conditional on the baseline score being below the cutoff. β2 captures the effect of crossing the cutoff threshold, providing an estimate of the intervention effect. Age and sex were included as control variables, represented by the coefficients β3 and β4, respectively. ϵ is the error term. We reported p-values based on robust standard errors, with all significant differences noted at $p<0.05$.

RESULTS

Table 4 presents the characteristics of the participants. The columns "Mean" and "SD or %" display the values for the complete dataset, excluding missing data. The "Missing n (%)" column shows the number and percentage of missing observations for each variable. The columns "Mean*" and "SD or %*" are based on the imputed data using a multiplication factor (M=100). A total of 6,382 individuals met the inclusion criteria. The average age of the participants was 73.5 years, with a standard deviation of 7.3 years, and 52.4% were women. The average baseline KCL score was 3.2, with the health status determined by the KCL score being robust at 65.6%, pre-frail at 22.6%, and frail at 11.9%. Missing data rates ranged from 13.9% to 27.2%. Therefore, MI methods were employed.

Figures 2 and 3 illustrate the KCL scores for the following year relative to the baseline KCL scores. The vertical line at KCL=4 represents the threshold for pre-frailty and the line at KCL=8 represents the threshold for frailty. These cutoff points were used to divide the participants into non-intervention and intervention groups. A discontinuous drop in KCL scores at both thresholds was observed in the subsequent year, indicating the need for validation using an RDD.

The RDD results regarding the effects of the message notification interventions are presented in Tables 5 and 6 for pre-frailty and frailty, respectively. A sensitivity analysis was conducted using three different bandwidths to compare the outcomes. The intervention effects were evaluated using various models. Model 1 was unadjusted, Model 2 was adjusted for baseline age and sex, and Model 3 used MI to handle missing values with adjustments. Models 1 and 2 were analyzed based on complete data.

Table 4. Participant characteristics (n=6,382)

Variables	Mean	SD or %	Missing n (%)	Mean*	SD or %*
Age, years	73.5	7.3	0.0		
Age ≥65, n (%)	3,865	60.6	0.0		
75≤ Age >85, n (%)	1,915	30.0	0.0		
Age ≥85, n (%)	602	9.4	0.0		
Female, n (%)	3,342	52.4	0.0		
BMI, kg/m^2	22.8	3.1	890 (13.9)	22.8	3.1
Baseline KCL total score	3.2	3.5	1,735 (27.2)	3.6	3.8
Robust: KCL ≤3, n (%)	3,047	65.6		3,912	61
Pre frailty: 4≤KCL ≤7, n (%)	1,048	22.6		1,527	24
Frailty: KCL ≥8, n (%)	552	11.9		943	15

SD: standard deviation; BMI: body mass index; KCL: Kihon Checklist. *Multiple imputation data (M=100).

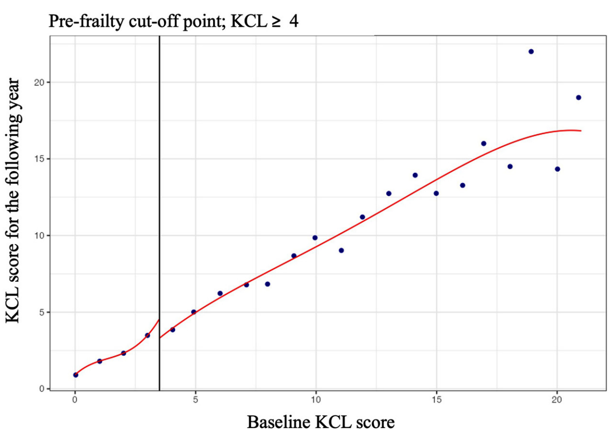

Fig. 2. Effect of message notifications on KCL score in the following year in the pre-frailty group
KCL: Kihon Checklist

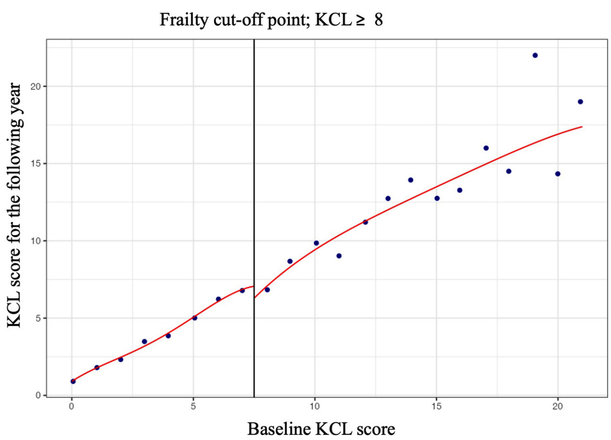

Fig. 3. Effect of message notifications on KCL score in the following year in the frailty group
KCL: Kihon Checklist

Table 5. Effect of message notification intervention on reducing KCL scores in the following year for pre-frailty

	Coefficients	SE	95% CI LL	95% CI UL	p-value	Observations
Model 1: Unadjusted model						
Bandwidth 2 (optimum)	−0.48	0.23	−0.93	−0.03	*	2,154
Bandwidth 3	−0.33	0.19	−0.71	0.05		3,119
Bandwidth 4	−0.13	0.19	−0.49	0.24		3,190
Model 2: Complete data analysis model, adjusted for baseline age and sex						
Bandwidth 2 (optimum)	−0.52	0.23	−0.97	−0.07	*	2,154
Bandwidth 3	−0.34	0.19	−0.72	0.03		3,119
Bandwidth 4	−0.15	0.18	−0.51	0.22		3,190
Model 3. Multiple imputation model (M =100), adjusted for baseline age and sex						
Bandwidth 2 (optimum)	−0.26	0.20	−0.65	0.13		3,756
Bandwidth 3	−0.19	0.17	−0.51	0.14		5,252
Bandwidth 4	−0.09	0.15	−0.38	0.21		5,576

SE: standard error; CI: confidence interval; LL: lower limit; UL: upper limit. *p<0.05.

Table 6. Effect of message notification intervention on reducing KCL scores in the following year for frailty

	Coefficients	SE	95% CI LL	95% CI UL	p-value	Observations
Model 1: Unadjusted model						
Bandwidth 2	−1.22	0.62	−2.44	−0.01	*	658
Bandwidth 3	−0.63	0.52	−1.65	0.39		963
Bandwidth 4 (optimum)	−0.45	0.46	−1.35	0.45		1,345
Model 2: Complete data analysis model, adjusted for baseline age and sex						
Bandwidth 2	−1.12	0.61	−2.32	0.08		658
Bandwidth 3	−0.63	0.52	−1.63	0.38		963
Bandwidth 4 (optimum)	−0.40	0.45	−1.29	0.49		1,345
Model 3. Multiple imputation model (M =100), adjusted for baseline age and sex						
Bandwidth 2	−0.33	0.38	−0.88	0.38		1,483
Bandwidth 3	−0.16	0.33	−0.80	0.48		2,144
Bandwidth 4 (optimum)	−0.03	0.28	−0.58	0.53		2,904

SE: standard error; CI: confidence interval; LL: lower limit; UL: upper limit. *p<0.05.

For the intervention on pre-frailty, both the unadjusted and adjusted models showed that the intervention reduced the KCL score in the following year, particularly at bandwidth 2 ($p<0.05$). However, these effects diminished when the MI model was used and no statistically significant results were obtained. A sensitivity analysis was used to assess the impact of the intervention using different bandwidths (bandwidths 2, 3, and 4). At bandwidth 2 (the optimal bandwidth), all models except Model 3 showed a statistically significant effect of the intervention on reducing the KCL score. However, as the bandwidth increased (bandwidths 3 and 4), this effect weakened and statistical significance was lost.

For the frailty intervention, only Model 1 at bandwidth 2 showed a significant reduction in the KCL score in the following year ($p<0.05$). No significant results were obtained for the other models with the adjusted covariates. We used a sensitivity analysis to compare the intervention effects using different bandwidths (2, 3, and 4). In Model 1, the statistical significance was lost with wider bandwidths, and no significant results were obtained in the other models across all bandwidths.

Subsequently, the variability of the intervention effects based on participants' demographic characteristics was examined by means of a subgroup analysis. Tables 7 and 8 present the results for pre-frailty and frailty, respectively. Subgroups were further divided according to age at a threshold of 75 years, sex, and survey year. In the analysis of complete data for pre-frailty, a reduction in the KCL score in the following year was observed among the groups aged >75 years, men, and the 2019–2020 group ($p<0.05$). However, these effects were diminished in the MI analysis, and no statistically significant results were observed.

In the analysis targeting frailty, a reduction in the KCL score was observed in the 2019–2020 data ($p<0.05$). However, no statistically significant results were obtained in the MI analysis.

DISCUSSION

The primary objective of this study was to evaluate the impact of health maintenance interventions using text messages on the health status of older adults classified as pre-frail or frail, using the KCL score as an evaluation index. We adopted an RDD approach to achieve this objective, which separated the intervention and control groups based on specific KCL score

Table 7. Subgroup analysis of the effect of message notification intervention on reducing Kihon Checklist (KCL) scores in the following year for pre-frailty

	Model	Coefficients	SE	95% CI LL	95% CI UL	p-value	Observations
Age groups adjusted for sex							
Under 75 years	CD	−0.32	0.29	−0.89	0.24		1,491
	MI	−0.19	0.23	−0.65	0.27		2,409
Over 75 years	CD	−0.79	0.38	−1.53	−0.05	*	663
	MI	−0.32	0.33	−0.97	0.33		1,334
Sex groups adjusted for age							
Men	CD	−0.63	0.32	−1.25	−0.01	*	1,136
	MI	−0.34	0.29	−0.90	0.22		1,811
Women	CD	−0.31	0.33	−0.96	0.34		1,018
	MI	−0.13	0.26	−0.65	0.65		1,940
Survey year adjusted for age and sex							
2019–2020	CD	−0.74	0.26	−1.24	−0.24	*	1,889
	MI	−0.38	0.21	−0.80	0.04		3,292
2020–2021	CD	0.09	0.22	−0.35	0.53		2,009
	MI	0.01	0.20	−0.39	0.41		3,468
2021–2022	CD	0.38	0.23	−0.07	0.84		2,120
	MI	0.18	0.21	−0.22	0.58		3,394

Analyzed with the calculated optimum bandwidth (bandwidth=2).
CD: complete data analysis model; MI: multiple imputation model; SE: standard error; CI: confidence interval; LL: lower limit; UL: upper limit. *$p<0.05$.

Table 8. Subgroup analysis of the effect of message notification intervention on reducing Kihon Checklist (KCL) scores in the following year for frailty

	Model	Coefficients	SE	95% CI LL	95% CI UL	p-value	Observations
Age groups adjusted for sex							
Under 75 years	CD	−0.69	0.74	−2.15	0.77		793
	MI	−0.18	0.51	−1.18	0.83		1,442
Over 75 years	CD	−0.24	0.57	−1.35	0.87		552
	MI	−0.03	0.39	−0.79	0.73		1,427
Sex groups adjusted for age							
Women	CD	−0.14	0.65	−1.40	1.13		630
	MI	0.14	0.36	−0.56	0.84		1,551
Men	CD	−0.70	0.63	−1.94	0.54		715
	MI	−0.16	0.44	−1.03	0.71		1,352
Survey year adjusted for age and sex							
2019–2020	CD	−1.25	0.57	−2.36	−0.15	*	816
	MI	−0.45	0.37	−1.16	0.27		1,897
2020–2021	CD	0.46	0.51	−0.54	1.46		908
	MI	0.21	0.34	−0.46	0.88		2,025
2021–2022	CD	0.05	0.53	−0.98	1.08		971
	MI	0.03	0.38	−0.71	0.77		1,987

Analyzed with the calculated optimum bandwidth (bandwidth=4). CD: complete data analysis model; MI: multiple imputation model; SE: standard error; CI: confidence interval; LL: lower limit; UL: upper limit. *$p<0.05$.

thresholds. The intervention had a slight effect on improving the KCL scores in the pre-frailty group. However, significant decreases were observed only for narrow bandwidths, and the effect diminished as the bandwidth increased. Additionally, the MI analysis did not show significant differences, suggesting that missing data substantially impacted the results.

Several factors may account for the small effect sizes observed in the present study. One reason for this is the message frequency. Previous studies have demonstrated that the frequency of message notifications significantly promotes health behaviors[8, 20]. For interventions involving multiple messages per day, the effect size was moderate, with Hedges' g=0.395. However, in our study, in which messages were sent only once per year, the effect was limited. Although there are limitations to sending messages by mail, increasing the frequency of messages as reminders could lead to substantial improvements in health behaviors. Another factor is message content. Aligning the content with nudging theory and the transtheoretical model of behavior change[21] and providing motivational messages for those who do not have an exercise habit and specific instructions for those who do, it is possible to provide step-by-step motivation and guidance at each stage of behavior change, potentially enhancing the effectiveness of future interventions. However, these considerations apply to the pre-frailty group because consistent improvements were not observed in the frailty group, suggesting that text messages alone may be insufficient for the frailty group. Direct intervention strategies and encouragement to participate in frailty prevention classes may be necessary to effectively address the needs of individuals with frailty.

The discrepancy between the results obtained from the complete data analysis and those after MI highlights the potential bias introduced by missing data. As is well known in the field of public health, individuals with high health awareness tend to actively participate in health check-ups, while those with low health awareness do not, creating a selection bias in health check-up surveys[22]. Participants without missing survey items responses in their complete data were likely to be highly motivated and conscious about their health, whereas those with missing data may have faced more severe health issues or socioeconomic challenges. This discrepancy may have led to the reduced observed effectiveness of the intervention in the MI model[23, 24]. Non-cooperative participants in the survey might have been less interested in health, suggesting that the messages may be less effective for this group. More direct surveys and information, such as home visits and interviews, may be required.

The subgroup analysis revealed that the intervention was particularly effective for certain groups, namely individuals aged 75 years and older, men, and participants enrolled from 2019 to 2020. This suggests that the intervention matched the specific needs and circumstances of these groups well. For instance, although adherence to mHealth interventions is generally lower among individuals aged 75 years and older[25], the older adults in this study may have found tailored guidance particularly beneficial to health maintenance. The notable effect among men, contrary to the general knowledge that health behaviors are typically more frequent in women[26], might be because men, who initially had relatively lower access to health information and lower health awareness, were more influenced by the awareness and specific behavioral instructions provided through the messages. Furthermore, the observed effect during the 2019–2020 period may be attributed to the initial impact of the municipality's efforts, where the novelty and uniqueness of the new initiatives and messages were particularly impressive for older adults. However, owing to insufficient data to analyze the influence of these subgroups in detail, further data collection and analysis are required in future studies.

This study has several limitations. First, the sensitivity analysis showed that the observed effects were influenced by changes in the bandwidth, with the effects diminishing as the bandwidth widened. This suggests that the heterogeneity of the target population did not meet the interchangeability assumption of the RDD. Therefore, the results of this study are limited to those near the threshold, and caution is required when generalizing the message effects to a broader population. Second, there were unmeasured confounding factors. Although the RDD can pseudorandomize unmeasured confounding factors, there are limitations to adjusting the model owing to restrictions on available covariates.

In conclusion, this study used an RDD to examine the effects of alert messages on older adults with pre-frailty and frailty. Although slight effects were observed in the pre-frailty group, further improvements could be achieved by adding reminders and improving message content based on the nudging theory. Direct intervention and special attention may be required for frail and high-risk individuals with missing data. The findings of this study provide valuable foundational information for designing and implementing health maintenance interventions in older adults.

Funding

This study received no external funding.

Conflict of interest

The authors declare no conflicts of interest.

ACKNOWLEDGMENTS

We express our sincere gratitude to the municipal government of Iiyama City, Nagano Prefecture, for providing the necessary data and support for this study. Their cooperation was invaluable in facilitating this study.

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