Does Smartphone Application Intervention Help People to Walk and Lose Weight? A Bayesian Estimation

Taisei Shiraishi s1260178 Supervised by Prof. Kenta Ofuji

Abstract

Using health checkup data from the Kansai Electric Power Company (KEPCO), I used Bayesian estimation-based analysis of variance to examine whether allowing employees to use an application that encourages walking exercise influenced their lifestyle behavior, particularly the number of steps they take.

I analyzed the effect of the use of the application on the rate of weight change in a sample (n=558) that had liver determination value data and no missing explanatory variables. I estimated that there was a positive correlation in the weight gain group and a negative correlation in the weight loss group, by categorizing the subjects by weight gain or loss. For the weight loss group, I estimated that the use of the application had an average effect of -0.97% in terms of weight loss.

However, the results of analysis also suggests that there is a large influence of individual differences other than the use of application, body size, smoking and drinking habits, and vegetable consumption habits that were considered in this study.

1. Introduction

In an aging society, it is important to utilize regular health checkup records. Our joint research partner, KEPCO, too, attempts to not just make the best use of such data, but also develop a smart-phone assisted health intervention program that encourages its employees to improve their daily living and exercise routines.

In this study, I statistically evaluated the effects of such intervention with health application, using KEPCO's medical checkup data.

2. Method

2.1. Data

In the analysis, I used two types of data: health checkup data from KEPCO and log data from the smartphone application Kenpos.

The health checkup data is the data of 9613 people who underwent health checkups in 2019 and 2020, and the Kenpos data is the time-series data of the number of steps and weight of 1240 application users.

Since there were many missing data in the data used, if there were any missing data in the variables handled in the analysis, I removed the data and use only the data without any missing variables were used.

In this study, I estimated the effect of the use of the application based on Bayesian estimation. Specifically, I evaluated how much the weight changed as a result of the exercise of walking prompted by the use of the application.

In the following, I analyzed the total set of three groups with improved, maintained, and deteriorated overall liver determination values (A1: healthy, A2: healthy but in need of attention, B: in need of further study, C: in need of treatment), which are related to alcohol consumption and exercise habits. This data set is hereafter referred to as the liver determination value group.

2.2. Analysis of variance

I adopted the analysis of variance model as the probability model. I defined the rate of change in body weight y_i as the response variable and seven explanatory variables: application usage x_1, BMI x_2, age x_3, overall judgment x_4, smoking x_5, alcohol consumption x_6, and food preference(vegetables) x_7. For employee i,

$y_i = \quad b_0$

$$+ b_1x_{1i} + b_2x_{2i} + b_3x_{3i} + b_4x_{4i} + b_5x_{5i} + b_6x_{6i} + b_7x_{7i} + e_i \quad (1)$$

b_1~b_7 are the respective coefficients, b_0 is the intercept, e_i is the error.

2.3. Bayesian Estimation

I estimate the effect of the application intervention by narrowing down the analysis to data sets with similar characteristics such as weight and age. Therefore, the sample size may become smaller due to the stratification of the data.

For example, if the sample is narrowed down to people whose liver determinations have deteriorated, the sample size is several dozen people. Therefore, I conduct the analysis based on Bayesian estimation, which can estimate confidence intervals even when the sample size is small.

In Bayesian estimation, the posterior distribution is obtained from the prior distribution according to Bayes' theorem. In this study, I use the MCMC (Markov Chain Monte Carlo) method, one of the random number generation algorithms, to generate random numbers that follow the posterior distribution obtained by Bayes' theorem. I conduct the analysis based on these random numbers.

3. Results

3.1. Analysis results for the liver determination value group

Table 1 shows the estimated results of the intercept, coefficients, and standard deviation of the analysis for the liver determination value group.

Table 1: Analysis results of liver determination value group

	Estimated value	Confidence interval (95%)
Intercept	1.68	-1.20~4.41
App usage: Use	-0.76	-1.87~0.36
BMI	-0.05	-0.13~0.03
Overall judgment value：A2	0.78	-0.40~1.96
Overall judgment value：B	1.14	0.35~1.92
Number of smoked cigarettes: 0~10 rolls	-0.77	-1.52~-0.03
Number of smoked cigarettes: 21~30 rolls	-0.29	-1.10~0.52
Number of smoked cigarettes: 31~40 rolls	-2.25	-4.02~-0.46
Number of smoked cigarettes: over 41 rolls	-1.42	-8.19~5.15
Amount of consumed alcohol: 0~1 cups	-0.42	-1.20~0.35
Amount of consumed alcohol: 2~3 cups	-0.30	-1.02~0.40
Amount of consumed alcohol: over 3 cups	0.55	-0.66~1.78
Food preferences (vegetables): Prefer	0.00	-0.59~0.60
Age	0.00	-0.04~0.03
Standard deviation	3.40	3.22~3.61

In table 1, the estimated values of the coefficients of the categorical variables each represent the difference from the criteria, based on the data in Table 2. For example, the estimated values of Overall judgment value: A2 and Overall judgment value: B represent the difference from Overall judgment value C.

Table 2: Criteria for coefficients in Table 1

Coefficient	Criteria
App usage	No use
Overall judgment value	C
Number of smoked cigarettes	11~20 rolls
Amount of consumed alcohol	1~2 cups
Food preferences (vegetables):	Not prefer

Figure 1 shows a graph of weight rate change by application usage. The length of the bars represents the 95% Bayesian confidence interval. In addition, "user" represents application users, and "non-user" represents application non-users.

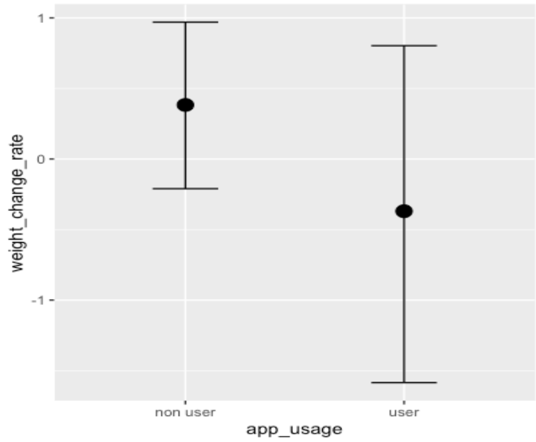

Fig. 1: Weight change rate by application usage

Figure 1 shows that the 95% Bayesian credit interval for application users is wider in the negative direction than for non-users. In other words, it shows that application user lose weight on average than the non-users.

Figure 2 shows the histogram for the weight change rate in the liver determination value group I analyzed (excluding the missing explanatory variables x1 to x7, the remaining n=558).

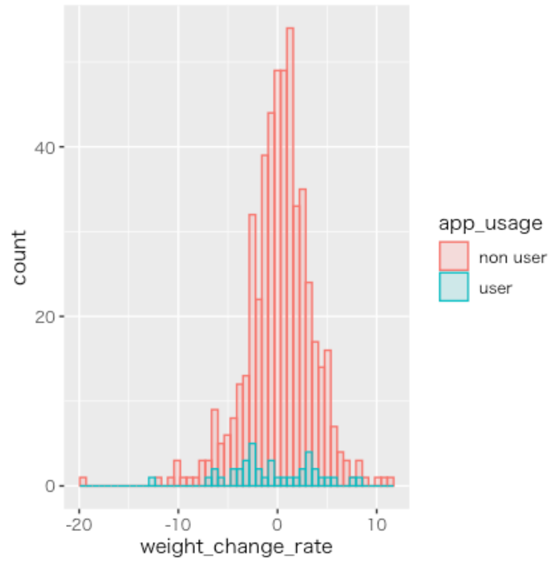

Fig. 2: Histogram of weight change rate of liver determination value group

Figure 2 shows that the data is divided into two mountains, one on the weight gain side and the other on the weight loss side, focusing on the data of the application users (blue) in the histogram in the figure. This suggests that the values of these two mountains cancel each other out in the analysis results for the liver determination value groups in Table 1. Therefore, I divided the sample into two groups (weight gain group and weight loss group) on the horizontal axis of Figure 2, with zero as the boundary. Then, I analyzed each group.

3.2. Weight gain group

Table 3 shows the calculation results for the analysis of the samples with increased body weight in the liver determination value group. For simplicity, I omitted the calculation results of coefficients other than application usage.

Table 3: Analysis results for the weight gain group

	Estimated value	Confidence interval (95%)
Intercept	4.43	2.17~6.62
App usage: Use	1.23	0.26~2.23
Standard deviation	1.99	1.84~2.17

Figure 3 shows the weight change rate for the weight gain group by application usage.

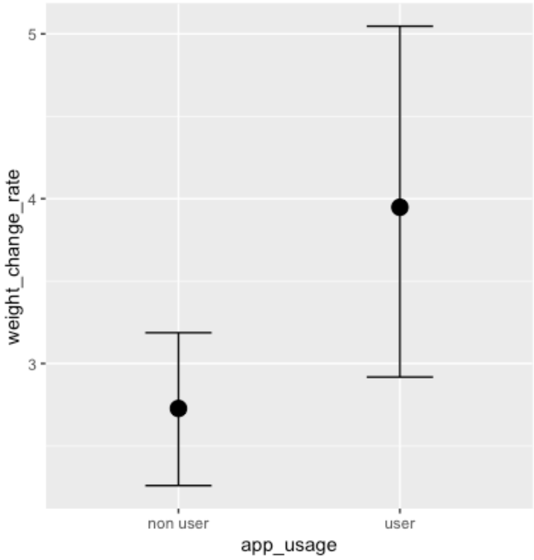

Figure 3: Weight change rate by application usage (weight gain group)

Figure 3 shows that in the weight gain group, the 95% Bayesian credit interval for application users (user) is wider in the positive direction than for the non-users. In other words, it shows that the weight of the application users has increased more on average than for non-users.

However, the "weight loss group" in the next section is more important in evaluating the effectiveness of the application.

3.3. Weight loss group

Table 4 shows the calculation results of the same analysis for the sample with reduced body weight in the liver determination group.

Table 4: Analysis results for the weight loss group

	Estimated value	Confidence interval (95%)
Intercept	-3.33	-6.66~-0.03
App usage: Use	-0.97	-2.16~0.19
Standard deviation	2.65	2.41~2.90

Since the coefficient for application usage was -0.97 and the Intercept was -3.33, I estimated that about 23% (-0.97) of the factors (-3.33-0.97 = -4.30) that affected weight loss were due to using the application. For example, if you weigh 60kg, you expect to lose about 1% of that weight, or about 600g on average, through the effect of using the application.

Figure 4 shows the weight change rate for the weight loss group by application usage.

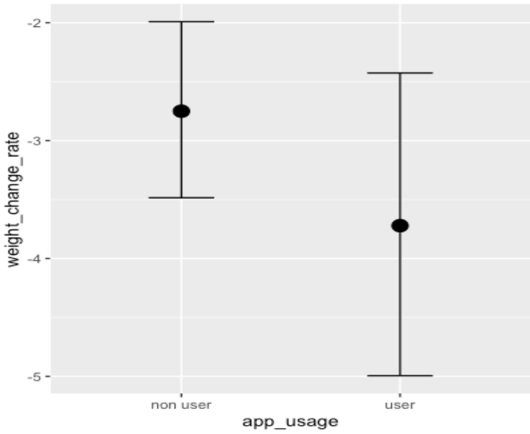

Figure 4: Weight change rate by application usage (weight loss group)

In the weight loss group, the 95% Bayesian confidence interval for the application users is wider in the negative direction than for the non-users. That is, it shows that the weight of the application users has decreased more on average than for non-users.

In this way, weight loss by application usage, which was not clearly visible for the group, became more visible by estimating the weight gain group/weight loss group separately.

In particular, it is important to note that in the weight loss group, there was an average weight loss of about 3.3%, and the use of the application boosted that by about 1%.

3.4. Difference in the number of steps taken by application users

Do people who have lost weight walk more and exercise more?

To find this out, I analyzed the difference in the average number of steps between weight gainers and weight losers for application users in the liver determination value group.

Figures 5 is the trace plots and posterior distributions of parameters visualizing the transitions of the generated MCMC samples for the weight gainers and weight losers, respectively.

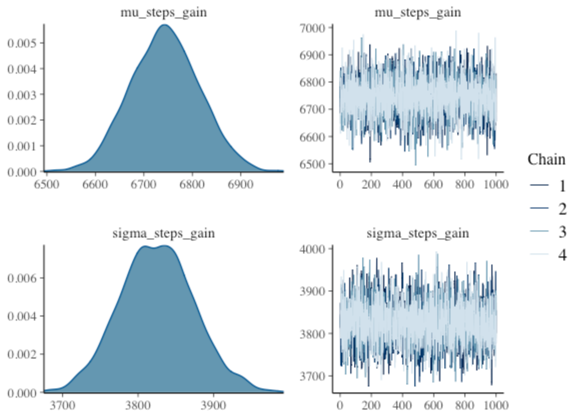

Figure 5: Posterior distribution of estimated parameters (weight gainers)

The "mu_steps_gain" and "sigma_steps_gain" in Figure 5 are the average number of steps taken by the weight gainers and the standard deviation of the number of steps taken by the weight gainers, respectively. From the figure, the mean value of the average number of steps "mu_steps_gain" is 6,743, and the mean value of the standard deviation "sigma_steps_gain" is 3,825 (Table 5). Table 5 also shows the 95% confidence interval.

Table 5: Average number of steps taken by app users (weight gainers)

	Estimated value	Confidence interval (95%)
The number of steps	6743	6606~6881
Standard deviation	3825	3729~3926

The same figure and table are provided for those with the weight losers (Figure 6, Table 6).

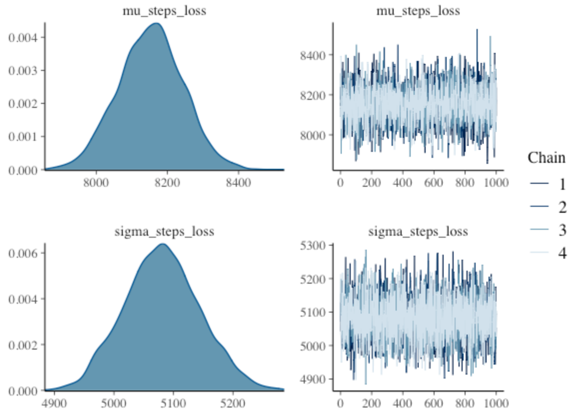

Fig. 6 Posterior distribution of estimated parameters (weight losers)

Table 6: Average number of steps taken by app users (weight losers)

	Estimated value	Confidence interval (95%)
The number of steps	8152	7974~8328
Standard deviation	5081	4963~5208

As a result of this analysis, I estimated that the average number of steps for the weight losers was 8,152 and the average number of steps for the weight gainers was 6,743. Namely, the weight losers walked about 1,409(8,152 - 6,743) steps more on average than the weight gainers during the period when they were using the application.

Thus, I confirmed that the weight losers were indeed walking and exercising a lot.

4. Conclusion

In the first analysis for the liver determination value group in Table 1, the data for the weight gainers and weight losers of the application users canceled out, and I did not successfully find an effect of the app intervention.

Therefore, I conducted a similar analysis by dividing the analysis targets into weight gainers and weight losers and estimated the effect of application use more clearly than the analysis for the entire group. As a result, I estimated the effect of application use more clearly than the analysis for the entire group.

I found that the effect of using application on the weight change rate is positively correlated in the weight gain group and negatively correlated in the weight loss group. However, the effect of the variables that were not treated in this analysis also appeared to be significant. As discussed in the main text, in the analysis of Table 4, Intercept was -3.33. This means that, on average, about 77% of the total factors that affected weight loss were due to variables that were not included in the analysis. In other words, more than the impact of using application, the impact of the user's health awareness and surrounding environment is significant. In addition, considering the effect of the use of the application varied depending on the increase or decrease in body weight, I speculate that the magnitude of the effect of the application intervention may also vary depending on the quality of the target.

As a future development, I plan to analyze the liver judgment value group by incorporating variables that were not handled in this study. I also plan to analyze the effect of application use in other group and to analyze the change in the effect of application intervention depending on the quality of the subject.

Acknowledgement

Finally, I would like to express my gratitude to my supervisor, Prof. Kenta Ofuji, who watched over my research until the end and gave me appropriate guidance. In addition, the R&D Office of Kansai Electric Power Company provided us with the data necessary for our research. I would like to express our sincere gratitude to them.

Reference

[1] Baba, Shinya (2019)Intro to Bayesian Statistical Modeling with R and Stan, Kodansha Publishing, Tokyo.