Original Paper

Automated Diet Management App Use and Health Outcomes in Japanese Employees: Panel Data Analysis

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Abstract

Background: Dietary habits are strongly associated with a wide range of health outcomes. Although professional interventions are effective, they are resource-intensive. Digital health apps provide a low-cost alternative, and accumulating evidence suggests their potential to improve health behaviors and outcomes. In Japan, some apps are covered by public health insurance; however, evidence from real-world use, particularly regarding both health outcomes and health care expenditures, remains limited.

Objective: This study aims to examine the relationship between the use of an automated diet management app and individual health outcomes, as well as health care expenditures, with a particular focus on the frequency of dietary self-monitoring behavior. Using real-world data from Japanese employees in a corporate setting, the study also seeks to provide evidence on the potential economic implications of digital health interventions and to provide evidence relevant to potential behavioral mechanisms underlying their effectiveness.

Methods: We constructed individual-level panel data (2021-2022) by linking app usage records, health checkup records, and medical claims records obtained through a health insurance association in a large Japanese corporate group. The main explanatory variable was the average number of daily meal records over the 90 days preceding the health checkup. We estimated the associations using fixed-effects panel models to control for time-invariant unobserved individual characteristics. Subgroup analyses by sex, age group, and baseline metabolic status were conducted to explore heterogeneity. Linear quantile regression was used as a supplementary analysis.

Results: More frequent use of the app was associated with a lower BMI among men (β=–0.126 kg/m², 95% CI –0.22 to –0.04; *P*=.001) and among women (β=–0.372 kg/m², 95% CI –0.54 to –0.20; *P*=.001). Among men, app use was also associated with improvements in waist circumference, blood pressure, and low-density lipoprotein cholesterol, whereas among women, it was associated with lower probabilities of metabolic syndrome and abnormal blood glucose. Associations with BMI were stronger among users aged ≤40 years and those with poorer baseline health. In contrast, among users aged ≥50 years, improvements were observed primarily in cardiometabolic risk factors rather than BMI. No statistically significant association was observed for short-term health care expenditures. Sensitivity analyses yielded generally consistent findings for the primary outcomes.

Conclusions: The findings suggest that digital diet management apps may contribute to statistically significant but modest improvements in health outcomes in workplace settings. However, given the observational nature of the study, the results should be interpreted as associations rather than causal effects. Overall, the findings highlight the potential of digital diet management apps as scalable interventions and underscore the importance of promoting sustained engagement and targeting populations most likely to benefit.

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Keywords: mobile health; diet management app; dietary self-monitoring; health promotion; biomarkers; medical expenses; panel data

Introduction

Eating habits are associated with several health problems such as obesity, hypertension, cardiovascular disease, and mental distress [1]. Interventions related to dietary content and eating habits positively affect health by preventing lifestyle-related diseases [2]. In particular, expert guidance (such as nutritional guidance from a dietitian) is highly effective [3-5] and can reduce medical expenses through disease prevention [6,7]. Even though personalized counseling is effective for implementing dietary interventions by specialists, it involves costs, including human and financial resources and time [8]. In addition, face-to-face intervention support involves issues, such as certain patients not wanting direct intervention from health care professionals [9-11] and certain patients dropping out of intervention support [12].

Health interventions using smartphone apps have become widespread owing to the rapid development of information and communication technologies. Several of these apps are provided free of charge or at low cost and can be used easily and conveniently by simply downloading them to one's digital device; thus, they are expected to be systems that promote autonomous health-promoting behavior. Recently, several studies examined the effectiveness of these health intervention apps, with a systematic review reporting that 50% to 61% of studies found improvements in outcomes such as weight and nutrient intake [13]. In addition, the higher frequency of app use has been associated with improved health outcomes [14]. Evidence on effective usage intensity suggests that during a 6-month experimental period, body weight can be reduced by 3% or more when the app is used on approximately 30% of days, by 5% or more on approximately 40% of days, and by 10% or more on approximately 70% of days [15]. Moreover, evidence based on large-scale longitudinal data indicates that regular use of health apps has a wide-ranging positive impact on employees' health status, health behavior, and work performance [16].

In Japan, public medical insurance began to cover specific therapeutic apps combined with doctor guidance in 2020. This was expected to improve treatment effects and effectively manage and provide continuous support for daily life habits among individuals with chronic diseases. By encouraging autonomous health-promoting behavior, the burden of face-to-face medical care for follow-ups can be reduced, and resources such as the time and medical space of medical professionals may be used more efficiently. In addition, the use of monitoring data from the apps may promote the early detection of diseases and prevent serious illnesses. This would result in reduced individual and macro health care costs. However, most existing studies on digital health apps rely on randomized controlled trials or short-term experimental settings. Evidence from real-world environments, particularly large-scale observational data reflecting actual user behavior in workplaces, remains limited. Furthermore, few studies have simultaneously examined both health outcomes and health care expenditures using these data [17]. As a result, the broader economic and policy implications of digital health apps remain insufficiently understood.

This study analyzed the associations between the use of an automated diet management app and individual health outcomes and medical expenses. In particular, we examined how the frequency of self-monitoring was associated with physical indicators such as BMI, biochemical markers, health checkup outcomes, and medical expenses. This study contributes to the literature in several ways. First, it evaluates the relationship between the use of a diet management app and health outcomes using real-world data from employees in a corporate environment, rather than controlled experimental settings. Second, the study examines both health outcomes and health care expenditures, providing evidence on the potential economic implications of digital health interventions. Third, by focusing on the frequency of dietary self-monitoring through an automated app, the study provides insights into the role of self-monitoring behavior in the observed associations between app use and health outcomes. These findings may provide useful implications for employers and health insurers considering investments in digital health tools to promote employee health and potentially reduce health care expenditures.

Methods

Automated Diet Management App

This study focused on an automated diet management app provided by Asken Inc. This app is a digital tool that supports the formation of healthy eating habits by allowing users to voluntarily record their meals via smartphones or other devices. The main functions are (1) meal recording, (2) nutritional analysis, and (3) personalized advice from experts. Users can log their meals using various input methods, and the recorded meals are matched with the food database containing more than 100,000 food items, and calories and nutrients are automatically estimated. In addition, a virtual nutritionist evaluates the nutritional balance of the day, identifies excessive or deficient nutrients, and provides personalized suggestions for improvement. The advice is automatically generated by a rule-based algorithm under the supervision of registered dietitians. The app also includes an automated image recognition function that assists in recording meals from food photographs.

The intervention evaluated in this study was the use of the dietary management app as an integrated intervention comprising multiple functions, including meal logging, nutrient visualization, automated dietary feedback, and AI-assisted image recognition for food entry. Because these components were provided simultaneously to users,

our study design does not allow their individual effects to be disentangled. Accordingly, this study does not estimate the independent behavioral effects of any specific app function. Although repeated meal logging, the automated dietary feedback generated from those records, and AI-assisted image recognition that facilitates meal logging by reducing recording burden may together represent an important behavioral pathway, the present study was designed to evaluate the overall effect of the integrated app rather than the contribution of its individual components.

Data Sources

The data are obtained from members of the health insurance association (hereafter, the association) of a Japanese corporate group that manufactures and sells electronic devices and is listed on the Tokyo Stock Exchange Prime. During the study period, the association covered more than 12,000 employees. According to the association, annual health checkups are provided to all insured employees, and the reported participation rate is approximately 100%. As part of its health promotion measures for employees, the association partnered with an app developer and introduced the app before the start of this study, providing it free of charge to employees who wished to use it. This research group signed a research and analysis agreement with the association and the app developer and received (1) data on the use of the app by association members (app records), (2) health checkup records, and (3) medical fee statement data (medical claims records). By linking these data on a per-member basis, the relationship between the use of this app and health conditions, medical expenses, etc, could be examined. Panel data was constructed for the 2 years (2021 and 2022). This study analyzed the effects of using the app on biochemical and physical indicators, health checkup results, and medical expenses.

The app usage records [18] included association members who had ever registered to use the app, regardless of whether they actively used it during the study period. The complete dataset covered records from April 1, 2021, to May 17, 2023. The database included personal identification numbers, dates of meal recording, indicators of whether breakfast, lunch, dinner, and snacks were recorded, and nutrient intake for each meal. Based on these records, the number of meal records was calculated for each participant. The exposure variable was then defined by linking the app records with the health checkup data as the average daily number of meal records during the 90 days preceding each participant's health checkup.

Health checkup records [19] included physical measurements, various test results related to biochemical indicators, and the doctors' examination and interview results (lifestyle, etc) at health checkups or full physical examinations for association members. In Japan, the Occupational Health and Safety Law requires employers to have their employees undergo health checkups, and employers bear the cost of these checkups. Therefore, it is difficult for selection bias to occur, given that individuals with a high level of health awareness are more likely to undergo health checkups and have better health. The data were collected between 2021 and 2022.

Medical claims records included the medical fees awarded to members, their age, sex, whether they were a member or a family member, and details of the illness for which they received treatment. The data collection period for the entire dataset ranged from medical treatment in April 2021 to medical treatment in January 2023. This study only used data on the members (excluding family members).

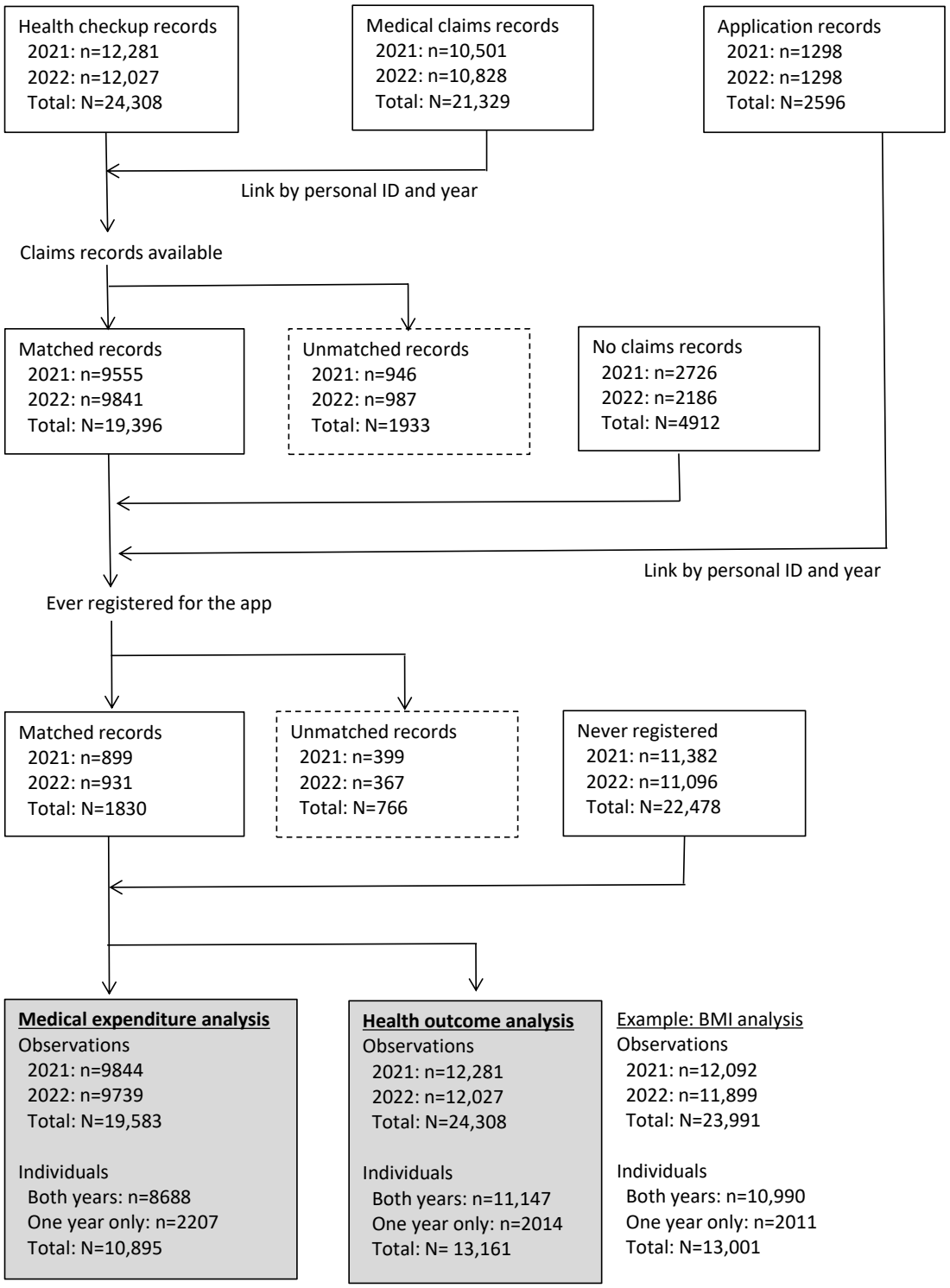
Study Population and Sample

The data used in this study consist of app usage records, health checkup records, and medical claims records, all of which are individual-level data identifiable at the personal level. These 3 datasets were linked using anonymized unique identifiers assigned to each insured individual within the health insurance system. For individuals whose app records could be successfully linked, the average number of meal records during the observation period was calculated.

Through the company's health program, all members were granted access to the paid version of the app free of charge. However, whether to register for the app was left to each employee. The initial app usage dataset comprised 2596 observations. However, approximately 30% of these records could not be linked to either the health check-up database or the medical claims database because of incorrectly registered, missing, or duplicated identifiers. According to the app provider, these identifiers could not be corrected retrospectively. Thus, linkage failure reflected technical limitations in the available data rather than intentional exclusion by the researchers. In this study, individuals who recorded at least one meal during the 90-day observation period prior to the health checkup were defined as "users." In contrast, individuals who had not installed the app, those with no meal records during the observation period, and those whose app records could not be linked because of these data limitations were all assigned a meal-recording frequency of zero and classified as "nonusers."

Because the primary focus of this study is actual self-monitoring behavior as captured by the frequency of meal logging, individuals with zero recorded entries were classified as nonusers regardless of whether they had installed the app. As a result, the fixed-effects analysis of health outcomes included 24,308 observations (13,161 individuals), whereas the fixed-effects analysis of medical expenses included 19,583 observations (10,895 individuals). The analytical sample differed across models because it depended on the outcome variables as well as the completeness of the covariates included in each model. Figure 1 illustrates the data linkage process and the derivation of the analytical samples.

Figure 1. Data linkage process and derivation of the analytical samples.



We controlled for year fixed effects to account for general time trends during the study period. In addition, annual workplace health checkups are conducted within a relatively narrow time window. More than 80% of the checkups were performed between June and August each year. Because the exposure variable was defined as app use during the 90 days preceding the health checkup, the observation window for app engagement was concentrated mainly between March and July. This design substantially reduces the influence of seasonal events (eg, holiday seasons) on both app use and health outcomes.

Ethical Considerations

This study was approved by the Research Ethics Committee of the Graduate School of Economics and Management, Tohoku University, on September 27, 2021.

Measurements

Outcome Variables

First, outcome variables included biochemical indicators obtained from health checkup data, namely systolic and diastolic blood pressure (mm Hg), fasting blood glucose (mg/dL), triglycerides (mg/dL), and low-density lipoprotein (LDL) and high-density lipoprotein (HDL) cholesterol (mg/dL), as well as physical indicators, including BMI (kg/m^2) and abdominal circumference (cm). This study focused on diet and eating habits that may be risk factors for metabolic syndrome. Based on the hypothesis that the more frequently this app is used, the better the health condition will be, this study predicted that the sign of the regression coefficient β_τ for the above data would be negative for systolic blood pressure, diastolic blood pressure, fasting blood glucose, triglycerides, LDL cholesterol, BMI, and abdominal circumference and positive for HDL cholesterol.

Second, this study established the following outcome variables: dummy variables for whether the individual met the criteria for metabolic syndrome, abnormal blood sugar results, and total medical expenses. The health checkup outcome for metabolic syndrome was defined as a binary variable that takes the value 1 if the individual meets the criteria and 0 otherwise. Similarly, the health checkup outcome for abnormal blood glucose was defined as a binary dummy variable, taking the value 1 for abnormal results (requiring further examination, re-examination, medical treatment, or follow-up observation) and 0 for normal results (no findings or within the normal range). Total medical expenses were defined as the cumulative medical expenses incurred during the 10 months following each participant's annual health checkup. The available claims data covered medical services provided between April 2021 and January 2023. Based on the hypothesis that the more frequently this app is used, the better the health checkup results and lower the medical expenses will be, this study predicted that the sign of the regression coefficient β_τ would be negative in all cases.

For binary outcomes, a linear probability model (LPM) was used. In the LPM, the coefficients can be directly interpreted as changes in probability per unit of exposure (average marginal effects), which has the advantage of facilitating interpretation in a fixed-effects panel framework. On the other hand, it is also known that the LPM has limitations, such as predicted probabilities potentially falling outside the 0-1 range and heteroskedasticity of the error term. In this study, the estimated coefficients are interpreted as approximations of average changes in probability, and these points should be taken into account when interpreting the results.

Exposure Variables

This study focused on the number of daily meals recorded (up to 3 times) and collected data on the average number of daily records (hereinafter, the average number of records) during the study period (90 d before the health checkups). The frequency of app use in this study is interpreted not as a direct measure of actual dietary intake but as a proxy indicator reflecting self-monitoring behavior. Daily app usage was defined as a maximum of 3 records corresponding to breakfast, lunch, and dinner, and the average number of daily records was calculated. Although users could also log snacks and between-meal items, these were excluded because of substantial individual variation in recording practices in order to maintain comparability in the intensity of self-monitoring.

Users could record meals using multiple methods, including text-based food name search, barcode scanning, and photo capture. Regardless of the input method, all records were converted into standardized food items linked to the app's food composition database. As the objective of this study is to evaluate the frequency of dietary self-monitoring rather than the detailed content of meals, and because the app does not distinguish between text and photo inputs, differences in input methods do not affect our analysis results.

The observation period for app records was defined as the 90 days prior to the health checkup. This choice is motivated by the fact that several metabolic indicators measured at health checkups reflect accumulated physiological conditions over weeks to months. In particular, HbA_{1c} is known to reflect average blood glucose levels over approximately the past 2 to 3 months [20,21]. In addition, app usage and self-monitoring behavior tend to fluctuate substantially in the short term; thus, using an observation window of several weeks or longer allows for the capture of sustained behavior rather than temporary increases in usage. Therefore, a 90-day observation period was adopted as a practical measure of recent dietary self-monitoring behavior. The proportion of individuals who recorded at least one meal was 17.3% (449/2596) within 90 days and 32.9% (854/2596) within 1 year, indicating that app usage was relatively infrequent. Using this data, this study examined whether individuals who used the app more frequently had better health or whether it had the effect of reducing medical expenses.

Covariates

This study used the following variables from the health checkup data: age, height, weight, a dummy variable for special notes in the medical history (a dummy variable that took the value of 1 if there were special notes in the medical history category in the health checkup data and 0 otherwise), a dummy variable for medication (a dummy variable that took the value of 1 if the individual was taking medication for blood pressure, blood sugar, or lipids and 0 otherwise), and a dummy variable for year (a dummy variable that took the value of 1 for the 2021 data and 0 for the 2022 data). In addition, the following lifestyle-related variables were used: regular exercise dummy (a dummy variable assigned a value of 1 if the individual exercised for 30 minutes or more twice a week for more than a year and 0 otherwise, based on the results of the health checkup interview); breakfast skipping dummy (a dummy variable assigned a value of 1 if the individual skipped breakfast 3 or more times a week and 0 otherwise); fast eating dummy (a dummy variable assigned a value of 1 if the individual "eats quickly compared to other people" and 0 otherwise); late-night eating dummy (a dummy variable assigned a value of 1 if the individual "eats dinner within 2 hours of going to bed" 3 or more times a week and 0 otherwise); and daily drinking dummy (assigned a value of 1 for "yes" and 0 for "no" regarding alcohol consumption frequency, categorized as "drinking every day" or "sometimes or hardly ever").

Statistical Analysis

Panel Data Analysis

This study created 2-year panel data to conduct an analysis using a fixed-effects model and a random-effects model and selected the model based on the Hausman test results. The estimation model can be presented as follows:

$$Outcome_{iy} = \alpha + \beta record_{iy} + \gamma X_{iy} + u_i + \varepsilon_{iy}, \quad (1)$$

Outcome is a variable related to biochemical and physical indicators, health checkup records, and medical expenses. *Record* is the daily average number of records. X is a vector of the covariates, and u is an individual effect. β and γ are vectors of the partial regression coefficients. This study focused on β, which shows the effect of the number of app records on the outcome. In addition, i represents individuals, y represents years, and ε is an error term. To focus on heterogeneity, a subgroup analysis was conducted by dividing the sample into male and female app users, by age (≤40 and ≥50 y), and by whether the previous year's criteria for metabolic syndrome were met. To evaluate the robustness of the main findings, we performed 3 sensitivity analyses: propensity score matching (PSM), one restricting the sample to ever-registered app users, and another replacing the continuous exposure measure with a binary indicator of app use during the previous 90 days.

Supplementary Analysis

Quantile regression was used as a complementary analysis to examine whether the association between app usage and health outcomes differs across the outcome distribution. This analysis is intended to provide descriptive insights into distributional heterogeneity rather than causal estimates comparable to the fixed-effects panel model. For quantile regression, the standard within transformation used in linear fixed-effects models cannot be directly applied, and fixed effects cannot be eliminated through simple differencing. These issues have been discussed as part of the incidental parameter problem [22]. When the number of time periods is small, it is difficult to consistently estimate individual fixed effects, and they suggest that identification in panel quantile regression is practically infeasible without a sufficiently large time dimension. Given the 2-period panel used in this study, quantile regression is treated as a supplementary analysis to examine heterogeneity across the outcome distribution rather than as a substitute for the main analysis. Heterogeneity was confirmed by capturing the differences in the effects of app use for each quantile, such as whether the effects of app usage were greater or smaller for individuals with poor health. The estimation model can be presented as follows:

$$Q_\tau(Outcome_i) = \alpha_\tau + \beta_\tau record_i + \gamma_\tau X_i + \varepsilon_{i,\tau}, \quad (2)$$

Q_τ ($Outcome_i$) is the τth quantile (τ=0.1, 0.2, …, 0.9) of the distribution of biochemical and physical indicators. *Record* is the average number of records, and X is a vector of control variables. β_τ is the effect of app use at quantile τ, and γ_τ is the effect vector of each regression coefficient at quantile τ. Moreover, i represents an individual, and ε is the error term.

Results

Descriptive Results

Table 1 presents the descriptive statistics for each variable. Table 2 compares the number of observations and mean values between app users and nonusers. App use was observed in 884 of 24,308 (3.6%) observations. In the unadjusted comparisons, statistically significant differences between app users and nonusers were observed for most outcome variables.

Table 1. Descriptive statistics.[a]

Variables	Observations	Mean (SD; range)
Average app recording frequency (times/day)	24,308	0.029 (0.262; 0.0-3.0)
BMI (kg/m^2)	24,307	23.405 (3.851; 0.0-51.6)
Waist circumference (cm)	20,459	83.427 (10.155; 55.0-156.0)

Variables	Observations	Mean (SD; range)
Diastolic blood pressure (mm Hg)	24,304	75.709 (11.955; 32.0-146.0)
Systolic blood pressure (mm Hg)	24,304	120.827 (16.376; 72.0-208.0)
LDL[b] cholesterol (mg/dL)	24,301	122.219 (30.437; 10.0-369.0)
HDL[c] cholesterol (mg/dL)	24,302	61.641 (16.011; 8.0-182.0)
Fasting blood glucose (mg/dL)	23,411	93.744 (14.703; 45.0-331.0)
Triglyceride (mg/dL)	24,300	111.673 (86.179; 12.0-1917.0)
Metabolic syndrome dummy	20,032	0.149 (0.356; 0.0-1.0)
Blood glucose abnormal dummy	23,388	0.885 (0.319; 0.0-1.0)
Medical expenses (JPY[d])	24,249	42,779 (102,634; 0.0-2,410,143)
Age (y)	24,308	45.773 (10.812; 18.0-73.0)
Male dummy	24,308	0.793 (0.405; 0.0-1.0)
Weight (kg)	24,307	66.988 (12.872; 31.1-170.4)
Height (cm)	24,307	168.857 (7.661; 122.2-196.7)
Medical history dummy	24,153	0.575 (0.494; 0.0-1.0)
Medication dummy	24,113	0.210 (0.407; 0.0-1.0)
Year dummy (2021)	25,552	0.506 (0.500; 0.0-1.0)
Regular exercise dummy	24,080	0.243 (0.429; 0.0-1.0)
Breakfast skipping dummy	24,076	0.248 (0.432; 0.0-1.0)
Fast eating dummy	24,090	0.339 (0.473; 0.0-1.0)
Late-night eating dummy	24,073	0.322 (0.467; 0.0-1.0)
Daily drinking dummy	24,129	0.240 (0.427; 0.0-1.0)

[a]Created by the authors based on app records, health checkup records, and medical claims records.
[b]LDL: low-density lipoprotein.
[c]HDL: high-density lipoprotein.
[d]JPY 1= US $0.008, based on the average of the 2021 and 2022 annual average exchange rates.

Table 2. Differences in mean values depending on whether or not the app was used.[a]

Variables	Observations		Mean values (SD)		Differences	*P* values
	Nonusers	Users	Nonusers	Users		
Average app recording frequency (times/day)	23,424	884	0.000 (0.000)	0.712 (0.974)	–0.712	<.001
BMI (kg/m^2)	23,423	884	23.416 (3.855)	23.113 (3.712)	0.304	.02
Waist circumference (cm)	19,716	743	83.471 (10.165)	82.274 (9.813)	1.197	.002
Diastolic blood pressure (mm Hg)	23,420	884	75.785 (11.964)	73.713 (11.557)	2.072	<.001
Systolic blood pressure (mm Hg)	23,420	884	120.947 (16.369)	117.644 (16.244)	3.304	<.001
LDL cholesterol[b] (mg/dL)	23,417	884	122.293 (30.427)	120.247 (30.64)	2.046	.05
HDL cholesterol[c] (mg/dL)	23,418	884	61.478 (15.951)	65.962 (16.953)	–4.484	<.001
Fasting blood glucose (mg/dL)	22,551	860	93.807 (14.710)	92.101 (14.44)	1.706	.001
Triglyceride (mg/dL)	23,416	884	112.037 (86.320)	102.031 (81.836)	10.007	.001
Metabolic syndrome dummy	19,313	719	0.150 (0.357)	0.102 (0.302)	0.049	<.001
Blood glucose abnormal dummy	22,522	866	0.884 (0.321)	0.917 (0.276)	–0.033	.003
Medical expenses (JPY[d])	23,369	880	42,352 (102,540)	54,128 (104,541)	–11,776	<.001
Age (y)	23,424	884	45.745 (10.784)	46.518 (11.507)	–0.773	.04
Male dummy	23,424	884	0.799 (0.401)	0.645 (0.479)	0.154	<.001
Weight (kg)	23,423	884	67.066 (12.882)	64.896 (12.435)	2.170	<.001
Height (cm)	23,423	884	168.920 (7.643)	167.183 (7.942)	1.737	<.001
Medical history dummy	23,274	879	0.571 (0.495)	0.670 (0.470)	–0.099	<.001
Medication dummy	23,234	879	0.210 (0.407)	0.204 (0.403)	0.006	.65
Year dummy (2021)	23,424	884	0.507 (0.5)	0.463 (0.499)	0.044	.01
Regular exercise dummy	23,202	878	0.241 (0.428)	0.302 (0.459)	–0.061	<.001
Breakfast skipping dummy	23,198	878	0.252 (0.434)	0.132 (0.339)	0.120	<.001

Variables	Observations		Mean values (SD)		Differences	*P* values
	Nonusers	Users	Nonusers	Users		
Fast eating dummy	23,211	879	0.339 (0.473)	0.344 (0.475)	–0.005	.78
Late-night eating dummy	23,194	879	0.324 (0.468)	0.257 (0.437)	0.067	<.001
Daily drinking dummy	23,249	880	0.241 (0.428)	0.222 (0.416)	0.020	.18

[a]Created by the authors based on app records, health checkup records, and medical claims records.
[b]LDL: low-density lipoprotein.
[c]HDL: high-density lipoprotein.
[d]JPY 1== US $0.008, based on the average of the 2021 and 2022 annual average exchange rates.

Results of Panel Data Analysis

The estimation results are presented in Tables 3 and 4. Subsample analysis was conducted by sex (male and female), generation (≤40 and ≥50 y), and whether or not the person met the metabolic syndrome criteria in the previous year (with metabolic syndrome and without metabolic syndrome). Those with metabolic syndrome refer to those who met the metabolic syndrome criteria in 2021, and those without metabolic syndrome refer to individuals who did not. This study analyzed how the app's effect differed depending on baseline health conditions. The estimation was performed using a fixed-effects model and a random-effects model, and the Hausman test results indicated that the fixed-effects model should be used in both cases. Before the main analysis, we compared linked and unlinked app records. Among app users, linked records had a significantly higher total number of meal records over the 2-year study period than unlinked records (mean 125.6, SD 279.1 vs 23.8, SD 124.4 records; *P*<.001). Because demographic characteristics such as age and sex were not collected in the most app usage records, comparisons of these characteristics between linked and unlinked records were not possible.

Table 3. Main results of panel data analysis.[a,b,c,d,e,f]

Average app recording frequency	BMI, β (95% CI)	Waist, β (95% CI)	Diastolic blood pressure, β (95% CI)	Systolic blood pressure, β (95% CI)	LDL[g] cholesterol, β (95% CI)	HDL[h] cholesterol, β (95% CI)
Male (n=19,015)	–0.126 (–0.22 to –0.04)[i]	–0.432 (–0.75 to –0.12)[i]	–0.979 (–1.80 to –0.16)[k]	–1.992 (–3.20 to –0.79)[i]	–3.456 (–5.40 to –1.52)[i]	0.388 (–0.30 to 1.08)
Female (n=4976)	–0.372 (–0.54 to –0.20)[i]	–0.571 (–1.35 to 0.21)	0.442 (–0.88 to 1.76)	–0.001 (–1.93 to 1.93)	–0.220 (–3.52 to 3.08)	–1.028 (–2.39 to 0.33)
≤40 years (n=13,729)	–0.321 (–0.45 to –0.20)[i]	–0.885 (–1.40 to –0.37)[i]	–0.024 (–1.07 to 1.02)	–0.338 (–1.80 to 1.12)	–2.071 (–4.47 to 0.33)[j]	0.254 (–0.70 to 1.20)
≥50 years (n=10,183)	–0.093 (–0.20 to 0.01)[j]	–0.293 (–0.67 to 0.08)	–1.098 (–2.08 to –0.12)[k]	–2.482 (–4.03 to –0.93)[i]	–3.199 (–5.68, –0.71)[k]	–0.321 (–1.16 to 0.52)
With MS[l] (n=2817)	–0.378 (–0.71 to –0.04)[k]	–0.970 (–2.06 to 0.12)[j]	–5.314 (–8.31 to –2.320[i]	–7.097 (–11.60 to –2.60)[i]	0.524 (–6.60 to 7.65)	1.788 (–0.22 to 3.80)[j]
Without MS (n=20,382)	–0.162 (–0.24 to –0.08)[i]	–0.377 (–0.68 to –0.07)[k]	–0.138 (–0.84 to 0.57)	–0.927 (–1.96 to 0.11)[j]	–2.830 (–4.52 to –1.14)[i]	–0.136 (–0.79 to 0.51)

[a]Estimates are presented separately by subsample (sex, age group, and baseline metabolic status) and by outcomes (BMI, waist, diastolic blood pressure, systolic blood pressure, LDL cholesterol, HDL cholesterol, fasting blood glucose, triglyceride, metabolic syndrome dummy, blood glucose abnormal dummy, and medical expenses).
[b]All models control for age, a dummy variable for special notes in the medical history, a dummy variable for medication, a year dummy variable, and lifestyle-related variables (regular exercise dummy, breakfast skipping dummy, fast eating dummy, late-night eating dummy, and daily drinking dummy; coefficients for these covariates are omitted for brevity).
[c]The values presented in the table are the regression coefficients for the exposure variable (the average number of meal records per day during the 90 days preceding the health checkup), and the values in parentheses indicate the 95% CIs.
[d]With MS (metabolic syndrome) refers to those who met the criteria for metabolic syndrome in the previous year, and without MS refers to those who did not.
[e]These estimation results were obtained using a fixed-effects model with panel data for 2021 and 2022.
[f]The subsample size shown corresponds to the analytic sample for BMI, which represents the largest available sample. Sample sizes vary slightly across outcomes due to differences in data availability.
[g]LDL: low-density lipoprotein.
[h]HDL: high-density lipoprotein.
[i]Statistical significance at the 1% level.
[j]Statistical significance at the 10% level.
[k]Statistical significance at the 5% level.
[l]MS: metabolic syndrome.

Table 4. Main results of panel data analysis (continued).[a,b,c,d,e]

Average app recording frequency	Fasting blood glucose, β (95% CI)	Triglyceride, β (95% CI)	Metabolic syndrome dummy, β (95% CI)	Blood glucose abnormal dummy, β (95% CI)	Medical expenses, β (95% CI)
Male (n=19,105)	–0.255 (–1.34 to 0.83)	–4.210 (–11.43 to 3.01)	–0.000 (–0.00 to 0.00)	–0.000 (–0.00 to 0.00)	–3913.4 (–15,727 to 7900)
Female (n=4976)	–0.324 (–1.87 to 1.22)	–0.661 (–7.01 to 5.69)	–0.000 (–0.00 to –0.00)[f]	–0.000 (–0.00 to 0.00)[g]	–5965.6 (–39,143 to 27,211)
≤40 y (n=13,729)	–0.136 (–1.41 to 1.14)	–4.059 (–12.27 to 4.15)	0.000 (–0.00 to 0.00)	–0.000 (–0.00 to 0.00)	–8204.3 (–24,742 to 8333)
≥50 y (n=10,183)	–0.324 (–1.71 to 1.06)	–2.488 (–10.80 to 5.82)	–0.000 (–0.00 to 0.00)[g]	–0.000 (–0.00 to 0.00)[g]	–2263.8 (–19,442 to 14,915)
With MS[h] (n=2817)	–1.710 (–7.72 to 4.30)	–19.170 (–51.32 to 12.98)	–0.000 (–0.00 to 0.00)	–0.000 (–0.00 to –0.00)[i]	–5219.3 (–45,916 to 35,477)
Without MS (n=20,382)	–0.141 (–0.90 to 0.62)	–1.270 (–6.63 to 4.09)	0.000 (–0.00 to 0.00)	–0.000 (–0.00 to 0.00)	–4008.4 (–15,940 to 7923)

[a]Estimates are presented separately by subsample (sex, age group, and baseline metabolic status) and by outcomes (BMI, waist, diastolic blood pressure, systolic blood pressure, LDL cholesterol, HDL cholesterol, fasting blood glucose, triglyceride, metabolic syndrome dummy, blood glucose abnormal dummy, and medical expenses).
[b]All models control for age, a dummy variable for special notes in the medical history, a dummy variable for medication, a year dummy variable, and lifestyle-related variables (regular exercise dummy, breakfast skipping dummy, fast eating dummy, late-night eating dummy, and daily drinking dummy; coefficients for these covariates are omitted for brevity).
[c]The values presented in the table are the regression coefficients for the exposure variable (the average number of meal records per day during the 90 days preceding the health checkup), and the values in parentheses indicate the 95% CIs.
[d] With MS (metabolic syndrome) refers to those who met the criteria for MS in the previous year, and without MS refers to those who did not.
[e]These estimation results were obtained using a fixed-effects model with panel data for 2021 and 2022.
[f]Statistical significance at the 1% level.
[g]Statistical significance at the 10% level.
[h]MS: metabolic syndrome.
[i]Statistical significance at the 5% level.

First, the estimation results for male, BMI, waist circumference, systolic blood pressure, diastolic blood pressure, and LDL cholesterol were significantly reduced as the average number of times the app was used increased. In women, BMI was significantly negative, and the regression coefficient values for the metabolic syndrome criteria and abnormal blood glucose judgment dummies reduced the probability of being applicable. However, the scale of these values was small. BMI was statistically significant in both men and women, and when comparing the scale of the regression coefficient values, the effect was slightly more significant among women. However, statistically significant relationships between several other biochemical indicators were only observed among men.

Second, age-stratified analyses showed distinct patterns of association. Among individuals aged ≤40 years, more frequent app use was significantly associated with reductions in BMI, waist circumference, and LDL cholesterol. Among those aged ≥50 years, significant associations were observed for BMI, blood pressure, LDL cholesterol, the probability of meeting the metabolic syndrome criteria, and abnormal blood glucose. Although BMI improved in both age groups, the estimated effect was larger among individuals aged ≤40 years, whereas improvements in several other metabolic indicators and physicians' assessment outcomes were observed mainly among individuals aged ≥50 years.

Third, this study analyzed how the effect of using the app differed depending on baseline health conditions. Regarding BMI and abdominal circumference, the more times the app was used, the lower the values became. Particularly, the regression coefficient values were approximately 2 times larger for individuals who met the metabolic syndrome criteria in 2021, indicating that the effect of using the app was more significant among individuals with poorer baseline health. In addition, the individuals who met the criteria for metabolic syndrome in 2021 had significantly lower blood pressure and a significantly lower probability of abnormal blood sugar. Moreover, the individuals who did not meet the criteria for metabolic syndrome in 2021 had significantly lower LDL cholesterol levels.

Sensitivity Analysis

To assess the robustness of the findings, we conducted 3 sensitivity analyses. First, we performed PSM based on baseline characteristics. The distribution of propensity scores indicated selection into app use; however, sufficient overlap between treated and control groups allowed for matching, and covariate balance improved substantially afterward. The matched sample size was greatly reduced, however (from 6496 to 248, a 96% reduction), and the estimated effects were generally not statistically significant. Given this substantial loss of power, this null result is difficult to interpret on its own and does not, by itself, rule out the possibility that residual self-selection into app use accounts for at least part of our main findings. The subsequent sensitivity analyses were conducted to further examine this possibility.

Second, restricting the sample to individuals who had ever registered for the app allowed us to hold self-selection into app registration constant and estimate the association based solely on variation in app use intensity among registered

users. This restriction reduced the sample size by a proportion comparable to that induced by PSM (eg, 93% among men). Nevertheless, the estimated regression coefficients retained the same sign as in the main analysis in 64 of the 66 outcome–subgroup combinations (97%). For BMI, waist circumference, blood pressure, and LDL cholesterol, the estimated effect sizes were also similar to those in the main analysis and did not attenuate toward the null as observed in the PSM analysis.

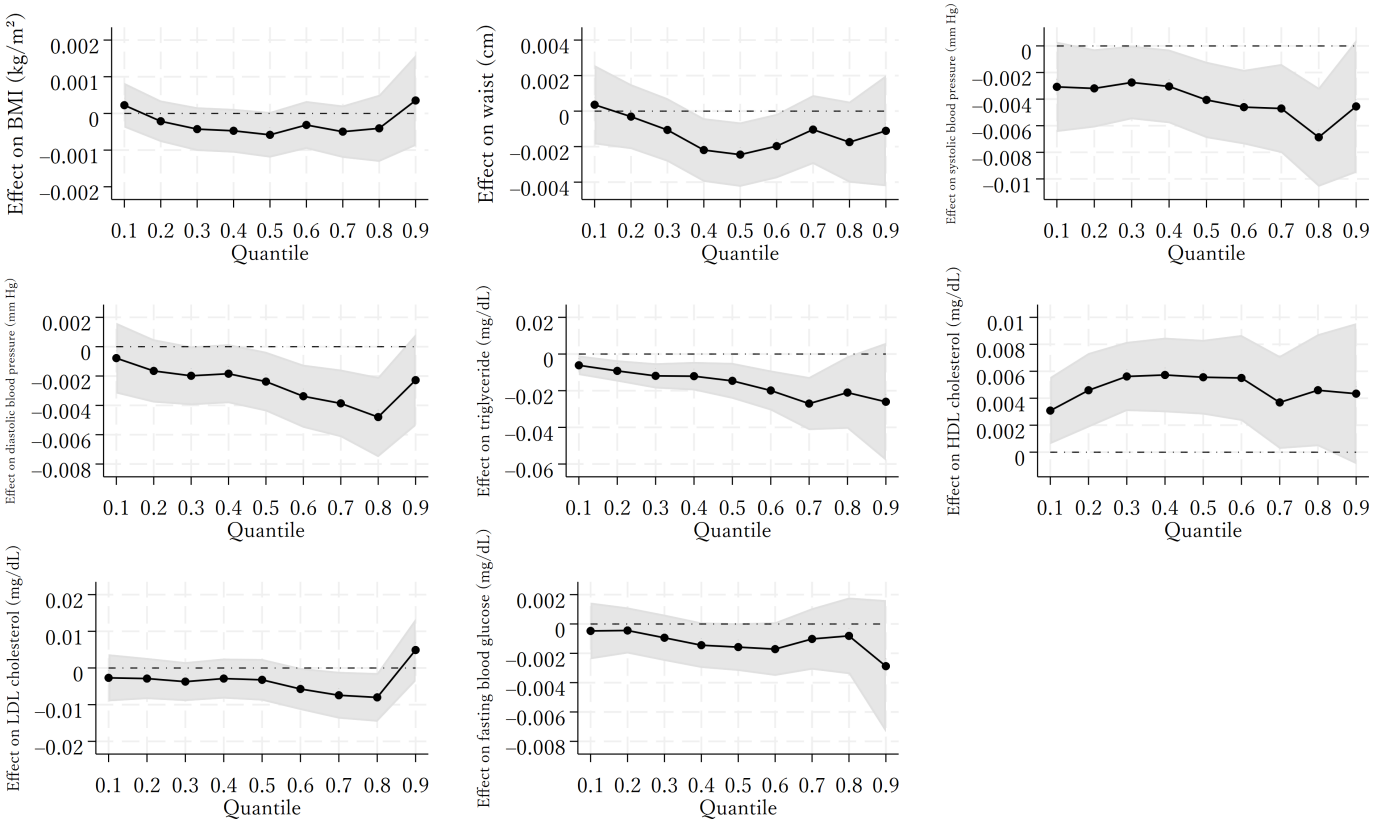
Third, replacing the continuous exposure measure with a binary indicator of app use in the previous 90 days yielded directionally consistent results for these same outcomes in most subgroups, although the consistency was somewhat lower, possibly reflecting the loss of information and statistical power associated with dichotomizing a continuous exposure measure. Full subgroup results for both analyses are reported in Multimedia Appendix 1 (Tables S1-S6).

As an additional robustness check, we also examined alternative definitions of app engagement, including the total number of records, the total number of days with records, and the average number of records during the period; these produced results broadly similar to those based on our primary exposure measure, the average number of records per day.

Results of Supplementary Analysis

As a reference, this study estimated the results using a linear quantile regression, which focused on heterogeneity. The results are illustrated in Figure 2. The vertical axis shows the regression coefficient values for each indicator, and the horizontal axis shows the 9 quantile points. Shaded areas indicate the 95% CIs. The sign of the regression coefficient for HDL cholesterol was positive. Conversely, the signs of the other indicators were generally negative, which was consistent with the hypothesis that the more the app is used, the better the health condition. Particularly, the higher baseline values for the blood pressure, triglyceride, and cholesterol-related indicators, the greater the effect of using the app. However, it should be noted that these are the results of an estimation using pooled data; therefore, the inherent effects that remain unchanged over time are not controlled for.

Figure 2. Estimation results using linear quantile regression. HDL: high-density lipoprotein; LDL: low-density lipoprotein.



Discussion

This study found that more frequent use of the automated diet management app to record meals was associated with significantly greater reductions in BMI across all subgroups. Subgroup analyses further revealed heterogeneous but coherent patterns: among men, app use significantly reduced abdominal circumference, blood pressure, and LDL cholesterol; among women, it significantly reduced the probability of being diagnosed with metabolic syndrome and abnormal blood glucose levels. Age-related differences were also observed. Among individuals aged 40 years or younger, significant reductions in abdominal circumference and LDL cholesterol were observed. In contrast, among those aged 50

years or older, the association with abdominal circumference was not statistically significant, whereas significant improvements were observed in blood pressure, LDL cholesterol, and the probability of being diagnosed with metabolic syndrome and abnormal blood glucose levels. In addition, the effects of app use were more pronounced among individuals with poorer baseline health. Taken together, these findings indicate a statistically significant but modest medical effect size, as reflected in the generally small regression coefficients. Because these results are derived from real-world data collected in a corporate setting rather than under controlled experimental conditions, they provide practical evidence that digital diet management apps may contribute to modest, real-world improvements in employee health.

In contrast, this study found no statistically significant short-term association between app usage and medical expenses. This null finding should be interpreted cautiously and may reflect several factors. First, the intervention effect may simply have been too small to translate into measurable reductions in medical expenses: although significant improvements were observed in BMI, abdominal circumference, blood pressure, and LDL cholesterol, the estimated effect sizes were generally modest and may not have been large enough to affect health care costs within the study period. Second, the observation period may have been too short relative to the time lag between behavioral change and cost reduction. Lifestyle interventions typically affect intermediate outcomes such as BMI, blood pressure, and glycemic control first, with reductions in chronic disease-related expenditures emerging only years later; prior studies have similarly found that the economic benefits of lifestyle interventions tend to materialize only after several years of follow-up [23-26]. Because medical expenses were tracked for only 10 months following the health checkup in this study, this period may have been insufficient to capture downstream cost savings.

A central aim of this study was to clarify the direction of the association between app use and outcomes of health and medical expenses. To reduce bias from unobserved individual characteristics, we used individual fixed-effects models, which control for time-invariant factors such as health preferences and health awareness, and conducted subgroup analyses stratified by baseline health status and individual attributes. We further assessed robustness through PSM and 2 sensitivity analyses. The PSM analysis, despite improving covariate balance, was substantially underpowered due to a marked reduction in sample size, and its null findings should therefore be interpreted with caution. Of the 2 sensitivity analyses, restricting the sample to ever-registered app users, which directly addresses self-selection into registration, produced results highly consistent with the main analysis despite a comparable reduction in sample size. Replacing the continuous exposure measure with a binary usage indicator showed somewhat greater variability, consistent with the expected loss of power from dichotomizing exposure, but pointed in the same direction as the main analysis for most primary outcomes and subgroups. Together, these robustness checks suggest that self-selection into app registration is unlikely to fully explain the observed associations. Nevertheless, as with all observational studies, time-varying unmeasured confounding cannot be ruled out entirely. Because the panel consisted of only 2 time points, we could not establish temporal ordering or fully exclude reverse causality. The findings should therefore be interpreted as associations rather than causal effects, and future research using longer panel data or more explicit identification strategies is needed to strengthen causal inference.

Several data limitations also warrant consideration. First, approximately 30% of app records could not be linked to the health checkup and medical claims records, primarily because of incomplete or incorrectly entered health insurance identification numbers at the time of app registration. Because unlinked records were treated as nonuse in the main analysis, some actual app users may have been misclassified as nonusers; consistent with this concern, linked app records showed a significantly higher total number of meal entries over the 2-year study period than unlinked records. The available data do not allow us to determine the direction or magnitude of the resulting bias. Second, the study sample was drawn from workers at a single corporate group with a strong commitment to use health promotion and may differ systematically from the average Japanese workforce; the findings may therefore not generalize beyond this population, and the potential for sampling bias should be considered when interpreting the results.

Additional uncertainty arises from how accurately app records reflect actual dietary behavior. Self-reporting bias, underreporting, and inconsistent compliance may all introduce measurement error, and this error is unlikely to be random: individuals may be less likely to log meals on busy days or during periods of weight gain, so missing or incomplete records may be systematically related to lifestyle conditions or health status. Conversely, individuals classified as nonusers (zero app usage) may have engaged in other health-promoting behaviors, such as using alternative health apps. To mitigate this concern, we adjusted for time-varying lifestyle factors obtained from physicians' interviews during the annual health checkup; however, because information on other health-related behaviors was unavailable, residual confounding from unmeasured health behaviors cannot be entirely ruled out.

This study cannot determine whether the observed associations were driven primarily by repeated self-monitoring through meal logging, by the automated personalized dietary feedback, or by their combination. Because feedback is generated only after meal logging, these two components operate as an integrated intervention in routine use and cannot be disentangled within the present observational design. Future studies comparing individual intervention components would help clarify the behavioral mechanisms underlying these associations.

Regardless of how advanced the underlying technology may be, systems that account for differences in user characteristics and behavior are essential for maximizing the effectiveness of such apps. It may also be valuable to

combine app use with complementary interventions that support behavioral change [27]. Future research should therefore examine the factors that motivate individuals to adopt and sustain use of these apps. From a policy and practical standpoint, evidence from real-world workplace settings such as this study may be particularly useful for employers, human resource departments, and health insurers considering investment in digital health tools to promote employee health and potentially reduce health care expenditures.

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Generative AI Use

ChatGPT (GPT-5 series, OpenAI) was used for language refinement and grammar checks to improve the clarity and readability of the manuscript. All AI-assisted content was reviewed and verified by the authors, who take full responsibility for the final manuscript.

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Data Availability

The datasets analyzed during this study are not publicly available due to confidentiality agreements with the collaborating organizations. The authors are not authorized to share these data with third parties.

Authors’ Contributions

Conceptualization: FO, HY, FC
Data curation: FO
Formal analysis: FO
Funding acquisition: FO, HY
Investigation: FO, HY, FC
Methodology: FO, HY, FC
Project administration: HY
Supervision: HY
Validation: FO, HY, FC
Visualization: FO
Writing – original draft: FO
Writing – review & editing: FO, HY, FC.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Sensitivity analyses of the association between dietary self-monitoring and health outcomes.
[PDF File (Adobe File), 500 KB-Multimedia Appendix 1]

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Abbreviations

HDL: high-density lipoprotein
LDL: low-density lipoprotein
LPM: linear probability model
MS: metabolic syndrome
PSM: propensity score matching

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